DISSERTATION

SOCIO-ENVIRONMENTAL TRADEOFF ANALYSIS USING DECISION SCIENCE TOOLS TO GUIDE RIVER MANAGEMENT

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ABSTRACT

SOCIO-ENVIRONMENTAL TRADEOFF ANALYSIS USING DECISION SCIENCE TOOLS TO GUIDE RIVER MANAGEMENT

Across the globe, rivers are put into the service of meeting human needs and wants. Societal dependence on rivers and the consumptive benefits they provide has advanced at the unanticipated cost of degrading biodiversity and river ecosystem function. Socio-environmental tradeoff analysis is key to balance disparate interests for sustainable river management. Multi-criteria decision analysis (MCDA) is a sub-discipline of decision science methods that aid decisions to resource management problems with multiple conflicting criteria and management alternatives. Techniques for MCDA are useful for tradeoff analysis but they are uncommonly used for river management, especially case studies based on incorporating the principles of river restoration into watershed management. I explore the qualitative and quantitative capabilities of MCDA with four stand-alone chapters that take a decision science approach towards balancing socio-environmental interests for large scale river management. Together, these chapters make a contribution toward bridging the gap between empirical freshwater science and normative decision making.

Chapter 1 - "Environmental flows" is a research discipline that emphasizes freshwater allocation in rivers to sustain desired ecological conditions and human wellbeing. The basis for determining environmental flow requirements has traditionally relied on hydrologic and ecological data and their relationships. Contemporary methods offer detailed hydro-ecological views of the river ecosystem. There is clear recognition of the need for incorporating social data

into environmental flows methods. However, there is currently no structured approach to systematically incorporate socially relevant data into the environmental flows discipline. In this chapter, the limitation is addressed with development of a conceptual diagram that applies a social-ecological systems approach to account for many criteria for environmental flows prescriptions. Translating criteria values into a common classification is described as valuable for river management case studies, and using these common classification in a systematic decision making process is recommended. A review of common MCDA methods is performed to understand method assumptions and to define appropriate decision contexts from which to gauge their usefulness for river management case studies.

Chapter 2 - The Ecological Limits of Hydrologic Alteration (ELOHA) framework takes a regional approach toward assessing relationships between human-caused river flow alterations and social-ecological benefits. ELOHA allows for, but does not specify, a social process with practical guidelines for incorporating social preferences into environmental flow management problems. Studies using the ELOHA framework are being performed around the world. This chapter presents development of a decision support tool to prioritize river basin criteria and to rank river segments in order of combined hydro-ecological and social environmental flow needs. We integrate this tool with hydro-ecological components of an ELOHA application in the Yampa-White River basin in northwest Colorado. Stakeholder preferences were collected with a survey and the analytic hierarchy process was applied to estimate the importance of five social-ecological criteria identified as valued proxies of freshwater management in the basin. Analytical methods for MCDA were used to integrate the preference information with results from the ELOHA application to prioritize the basin river segments. These methods and results provide a means to facilitate stakeholder negotiation and future environmental flow policy analyses. By extending the existing ELOHA framework to include a social preference component, this approach is general and can be applied to environmental flow policy and management in other river basins.

Chapter 3 - In this chapter, a decision framework is proposed for systematic river restoration planning. With the framework, key concepts of decision analysis are used to systematically design and formally evaluate Pareto efficient tradeoffs associated with alternative restoration strategies within a watershed, and to provide a short-list of viable restoration alternatives to decision makers for implementation. The proposed framework has the capacity to render technical science-based information and sophisticated decision making techniques more transparent for stakeholder deliberation and future restoration policies. To illustrate the framework, I draw from a published restoration case study in South East Queensland, Australia.

Chapter 4 – This chapter also draws from a previously completed restoration case study in Victoria, Australia, but describes a new method for MCDA to objectively prioritize water management alternatives that characteristically feature large multidimensional sets of criteria and alternatives. A combined simulation and multi-objective optimization procedure was previously integrated into a hydrologic catchment network. That process resulted in a large set of daily water allocation schedules that traded off long-term irrigation and hydro-ecological criteria performance at the catchment outlet. The new MCDA method includes combined multidimensional ordination and cluster analysis to spread many water allocations onto a two-dimensional plane and to discover alternatives with similar criteria tradeoffs. Compromise programming was performed on the full set of alternatives and on each cluster to rank the water allocation projects for a more simplified tradeoff analysis. This method complements the use of subjective elicitation procedures to describe the importance of water management criteria for inclusion in a MCDA.

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CHAPTER 1: A SOCIAL-ECOLOGICAL FRAMEWORK TO INTEGRATE MULTIPLE OBJECTIVES FOR ENVIRONMENTAL FLOWS MANAGEMENT

Portions of this chapter have appeared in print (Martin et al., 2014)

Summary

"Environmental flows" is a research discipline that emphasizes freshwater allocation in rivers to sustain desired ecological conditions and human wellbeing. The basis for environmental flow requirements has traditionally relied on hydrologic and ecological data. Contemporary methods focus on detailed hydro-ecological relationships within river ecosystems; however, there is currently no structured approach to systematically incorporate socially relevant information into the environmental flows discipline. To address this limitation we developed a flexible framework that applies a social-ecological systems approach to account for multiple flow-related objectives that reflect both biophysical sustainability and societal preferences. First, we conceptualize the freshwater SES as a hierarchy of human and environmental domains. Then, we recommend stepwise procedures to assess flow-related vulnerabilities of important system attributes, address their feedbacks, and translate these assessments to a common classification for comparative analyses that guide holistic flow management decisions. Translating criteria values into a common classification is described as valuable for river management case studies, which are uncommon. A review of common methods for multi-criteria decision analysis is performed to understand method assumptions and to define appropriate decision contexts from which to gauge their usefulness for river management case studies.

Introduction

Unique management challenges over freshwater have been developing throughout the world over the last century (Postel, 2000; Postel and Richter, 2003). Appropriation of freshwater from rivers to meet human needs and socioeconomic development is made difficult by withdrawals for competing demands (Gleick, 1998; Poff et al., 2003; Vörösmarty et al., 2010) and from external climate drivers (Beniston, 2003; Bates et al., 2008). Additional pressures are put on the availability of freshwater resources for non-consumptive uses like recreation and environmental conservation. Recent legal recognition of the "beneficial use" of non-consumptive needs for instream flows in U.S. state statutes (Mathews, 2006) is an important step towards legitimizing the preservation and restoration of healthy, functioning river ecosystems (Baron et al., 2002).

"Environmental flows" is a science-based discipline that emphasizes the beneficial use of instream flows in rivers. The discipline has developed out of growing knowledge that the ecology of rivers is coupled with natural patterns of streamflow variability; this is formalized in Poff et al. (1997) as the natural flow regime paradigm. Environmental flows research typically begins by using daily stream gauge data to derive and compare flow regimes in river hydrographs, which are graphical depictions of fluctuating river discharges per unit time (Figure 1.1). Hydrographs are fundamental for establishing flow-ecology relationships (Poff et al., 2010), which describe how ecological variables change in response to deviations in flow from natural or baseline conditions. These relationships require two basic steps. First, the statistical derivation of flow metrics (Richter et al., 1996; Olden and Poff, 2003) explain important disturbance characteristics of the flow regime such as magnitude, frequency, seasonal timing, duration, and rate of change. Second, flow metrics are used to model hypothesized effects on the biophysical components of a river system (Arthington et al., 2006; Poff et al., 2010).

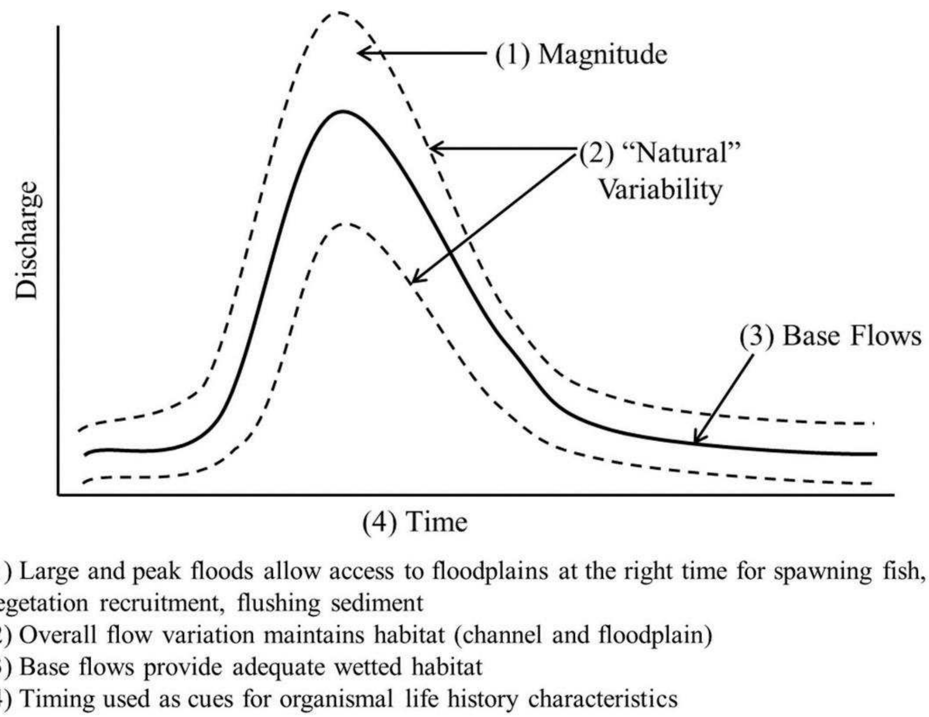

Figure 1.1 Example of a river hydrograph, typical flow regime characteristics, and examples of hypothesized effects on the biophysical components of the river system. We illustrate with four typical flow regime characteristics and examples of the hypothesized effects. This hydrograph is typical of snowmelt-driven (unimodal) runoff of the American West; other regions have characteristically similar runoff and unique hydrographs from which to guide ecological hypotheses (see Poff et al., 1997).

The natural flow regime provides a range of flow characteristics that facilitate conditions responsible for maintaining ecological structure and function of rivers and streams (Poff et al., 1997). Natural disturbances and human impoundments like dams and diversions cause alterations to the flow regime, which impair the distribution and abundance of aquatic organisms, physical-chemical water quality, and the ecological integrity (i.e., unimpaired condition) of the river ecosystem. Several mechanisms that underlie these impairments include (Bunn and Arthington, 2002): i) undesirable modifications to river biophysical habitat and processes; ii) loss of life history cues for aquatic organism survival and recruitment; iii) loss of longitudinal and lateral connectivity upstream, downstream, and across the river and its floodplain; and iv) encouraging exotic species proliferation. An environmental flow requirement (EFR) (Tharme, 2003) is a flow regime that targets desired ecological conditions through statistical deviations between a river's un-altered and altered flow regime. Flow-ecology relationships are used to prescribe EFRs and can be visualized as statistical trade-offs between percent flow alteration and ecological condition.

The methods for establishing EFRs were traditionally driven by hydrologic and biophysical data requirements for small-scale river flow management. The earliest holistic methods embodied an ecosystem-based management approach but lacked social aspects (Poff and Matthews, 2013). Contemporary holistic methods extend management considerations to societal and ecological objectives. Although the holistic methods advocate multiple freshwater needs, they lack structured approaches to assimilate and screen different types of data.

This chapter extends the current practice of holistic environmental flows management to include an understanding of societal objectives expressed through socioeconomic data. We frame this discussion by beginning with a historical assessment of hydrological and biophysical considerations for flow management. Next, we review several contemporary and holistic methods that integrate socioeconomic data to assess common currencies of how flow alterations affect societal objectives. Based on these reviews, we present a conceptual framework that systematically assimilates relevant data from societal and ecological objectives to support holistic environmental flows management. Methods for multi-criteria decision analysis (MCDA) are identified as appropriate integration tools to support a balance of social-ecological interests for river flow management.

Traditional criteria for environmental flows: hydrologic and biophysical data

Hundreds of methods for assessing environmental flows have been developed to address river ecosystem condition (Tharme, 2003). Most methods involve a simplified assessment of the river ecosystem and the development of flow-ecology relationships for biotic and abiotic conditions. The methods fall into four general classes: hydrologic, hydraulic rating, habitat simulation, and holistic methods (Tharme, 2003; Acreman and Dunbar, 2004). Each class of methods has a common conceptual basis for their approach but often differ in their data requirements or in their selection of flow regime metrics to model flow-ecology relationships (Table 1.1). Hydraulic rating methods, for example, typically assume a strong importance on geomorphology and physical habitat characteristics like river depth, velocity, and sediment substrate. All classes of environmental flows methods require instream flow data that are typically provided by stream gauge measurements.

Table 1.1 Selected reference list of environmental flow methods and relevant data by class. Information in this table is a sub-set of methods and is provided to illustrate the breadth of the existing knowledge base and data requirements.

Class	Example Methods	Relevant Data	Metrics	Source
Hydrologic	Tennant Method	Percentage of mean annual flow (MAF) for two six month seasonal periods	Recommended % of MAF	Tennant, 1976
	Range of Variability	Multiple years of daily flow records (e.g. stream gauge, groundwater wells)	32 statistically-derived hydrologic metrics	Richter et al., 1996, 1997
	"Percent of Flow" approaches	Observed or modeled "unaltered" daily flows	% deviation above and below "natural" flow regime	Richter et al. 2012
Hydraulic Rating	Wetted Perimeter Method	Cross-section width of the stream bed and banks in contact with water for various discharges;	Relationship between discharge and wetted perimeter	Gippel and Stewardson, 1998
	R-2 Cross Method	Hydraulic parameters for mean depth, percent of bankfull wetted perimeter, and average water velocity	Plots of wetted perimeter vs. discharge	Nehring, 1979
Biophysical Habitat	Instream Flow Incremental Methodology	Species data: preferred hydraulic habitat attributes by life history stage; channel geometry; modeled flow-hydraulic attribute relationships (PHABSIM)	Weighted Usable Area (WUA) versus discharge function	Stalnaker et al., 1995; Milhous, 1998
	Physical Habitat Simulation Model (PHABSIM)	Cross-section data: depth, velocity, substrate, cover, WUA	Habitat suitability indices	Milhous and Waddle, 2012
	Biological Response Modeling	Flow associations for macroinvertebrate taxa; flow parameters associated with community structure	Lotic invertebrate Index for Flow Evaluation	Extence et al., 1999
Holistic	Building Block Methodology	Discharge data; cross-section data: hydraulic characteristics, fish and macroinvertebrate data, riparian vegetation surveys;	Monthly flows that describe regime types to meet modeled ecological conditions	King and Louw, 1998
	Riparian vegetation-flow response guilds	hydrologic characteristics for stream classes; functional response traits of riparian plant species; empirical flow response guild relationships	Predictions for riparian trait occurrence; vegetation-flow response guilds	Merritt et al., 2010

Hydrologic methods represent the simplest of the four classes and typically describe acceptable or low flow discharge levels on the basis of a proportional streamflow volume. More sophisticated hydrologic methods incorporate additional criteria representing biological, hydraulic, or other desired endpoints tied to specific characteristics of the flow regime. For example, hydraulic rating methods assess relationships between discharge data and hydraulic variables (e.g., instream wetted width, depth) that are used to quantify thresholds for critical instream habitat (Acreman and Dunbar, 2004). This may include a specific magnitude and duration of flow required to mobilize instream sediment and/or scour the channel bed. More complex habitat simulation or physical habitat methods extend this idea to model how changes in discharge affect physical conditions that influence the habitat suitability for target organisms (Booker, 2003).

Traditional holistic methods have embodied the perspective of ecosystem-based management, emphasizing large-scale linkages between river, riparian, and wetland environments (Acreman and Dunbar, 2004). The earliest attempts to incorporate holistic methods established multiple EFRs that specified the timing of acceptable river flows needed to simultaneously achieve multiple environmental objectives like channel maintenance, habitat maintenance, and fish spawning and migration (King and Louw, 1998). Despite a focus on ecosystem-based management, most of the holistic methods do not include formal frameworks to incorporate socioeconomic data that capture societal perspectives on desired ecological endpoints.

Contemporary social contexts and relevant data

Environmental flows assessments have extended beyond the traditional hydro-ecological research domain into broader river management methods that integrate both ecosystem maintenance and societal objectives like water supply and recreation. In general, integration of societal objectives requires linking socioeconomic conditions with flow variables. In practice, this entails understanding how alterations to a river's hydrograph affect the ecosystem services or benefits supplied to society. For example, recreational visitor days for fishing or whitewater boating are potentially impacted by streamflow alterations (e.g., Daubert and Young, 1981). Socioeconomic data like these can be used to investigate relationships that describe how social benefits are related to important flow regime characteristics (Sanderson et al., 2012a). To date there are limited efforts to actively incorporate societal objectives into EFRs, despite the fact that such incorporation is critical for successful implementation of environmental flow targets (Poff et al., 2010; Pahl-Wostl et al., 2013). We review several common methods for their approaches to integrate socioeconomic data requirements into the environmental flows discipline.

The Ecologically Sustainable Water Management (ESWM) framework attempts to design and implement a water management program that establishes EFRs in an open dialogue among stakeholders (Richter et al., 2003). This framework is developed to a large extent on investigating how dams impact river ecology. ESWM has been used to rehabilitate flow regimes as storage release decisions that use the historical range of variability approach to EFRs (Richter et al., 1997).

The Downstream Response to Imposed Flow Transformation (DRIFT) is considered a holistic method that was established for water development projects in South Africa (King et al., 2003). DRIFT's decision support framework generates multiple scenarios that each describe alternative river ecosystem conditions with varying ecological and socioeconomic condition estimates (Brown and Joubert, 2003). This information can be used by decision makers for future watershed planning purposes. The sociological module within DRIFT allows for the assimilation of socioeconomic data like fish catch, vegetable harvest, and drinking water volume. The resulting relationships are explained as varying degrees of human health risk that correspond to alternative flow scenarios (King et al., 2003). The DRIFT framework relies on *a priori* communication with subsistence users of the river ecosystem.

The Ecological Limits of Hydrologic Alteration (ELOHA) framework supports large-scale watershed management by classifying hydrologically similar rivers as the basis for developing regional flow-ecology relationships (Poff et al., 2010). The ELOHA process occurs in two phases: i) a series of science-based steps that specify a regional hydrologic foundation, classification of river types using hydrologic or geomorphic data, and derivation of flow-ecology relationships with biological data; and ii) a social step that integrates societal management needs with EFRs to improve river management policy decisions. Current applications of this framework (Kendy et al., 2012) emphasize the importance of the ELOHA social process but offer limited guidance for taking steps to accommodate societal objectives.

A social-ecological systems approach to flow management

The contemporary methods for environmental flows management lack a structured approach to integrate ecological and socioeconomic data. Such a framework is needed to support multi-objective flow management. To address this limitation, we envision a screening process that accommodates multiple flow-ecology relationships and socially derived flow-related relationships. Our approach is through the research lens of social-ecological systems (SES), a discipline that conceives of managed systems as an aggregation of linked social (e.g., institutions, property rights, behavior) and ecological (e.g., environmental resources) sub-systems (Berkes and Folke, 1998). SES research integrates important information from these sub-systems by establishing relationships between ecological and social conditions.

First, we define the freshwater SES as a hierarchy of environmental and human organizational domains. The domains interact through feedbacks to influence overall system behavior, which we define as the ability to achieve a balance between desired societal and ecological objectives. Our characterization of a freshwater SES is based on human institutions for resource management (e.g., ethical and legislative rules, behavior) and adapted from the hierarchical decision systems approaches of Ciriacy-Wantrup (1967) and Ciriacy-Wantrup and Bishop (1975).

Our hierarchical representation of the freshwater SES (Figure 1.2) includes, at its foundation, the ecosystem, which provides goods and services that facilitate human endeavors at higher levels (Daily, 1997). Distinct operational and community domains within the second level of the hierarchy operate through direct interaction (i.e., monitoring and use) with freshwater ecosystems. Operational entities may include irrigation districts, water conservancy districts, academic institutions, dam operators, or water rights holders. The community refers to public elements such as water consumers and other beneficiaries reliant on flow-related sustenance and recreation (i.e., ecosystem services). The institutional domain consists of members who regulate the operation and use of water resources (e.g., Bureau of Reclamation, U.S. Army Corps of Engineers) and conduct appropriate assessments of the freshwater ecosystem (e.g., Environmental Impact Statements). The policy domain of the hierarchy may grant or restrict rights and change the regulating responsibilities of the institutional domain like state soil and water conservation boards, the Environmental Protection Agency, or the use of Threatened and Endangered Species Act designations.

To understand how a freshwater SES functions, identification of system boundaries is followed by an assessment of system performance indicators we term “attributes.” System boundaries are defined for each management context. For watershed-based management, the system may be defined at multiple scales depending on the management objectives. For example, Beechie et al. (2010) partition a catchment into watershed and reach scales for defining distinct ecological outcomes. Attributes of a freshwater SES serve as comprehensive, measurable, and manageable proxies for management objectives. We select socially desirable attributes on the basis that they are amenable to flow management decisions.

We developed a framework that extends a SES approach to integrate many types of data into the environmental flows discipline (Figure 1.2). Our goal with the framework is to provide a systematic account of relevant water data from relevant domains of a freshwater SES and to use the data to assist in integrated environmental flows studies and decision-making.

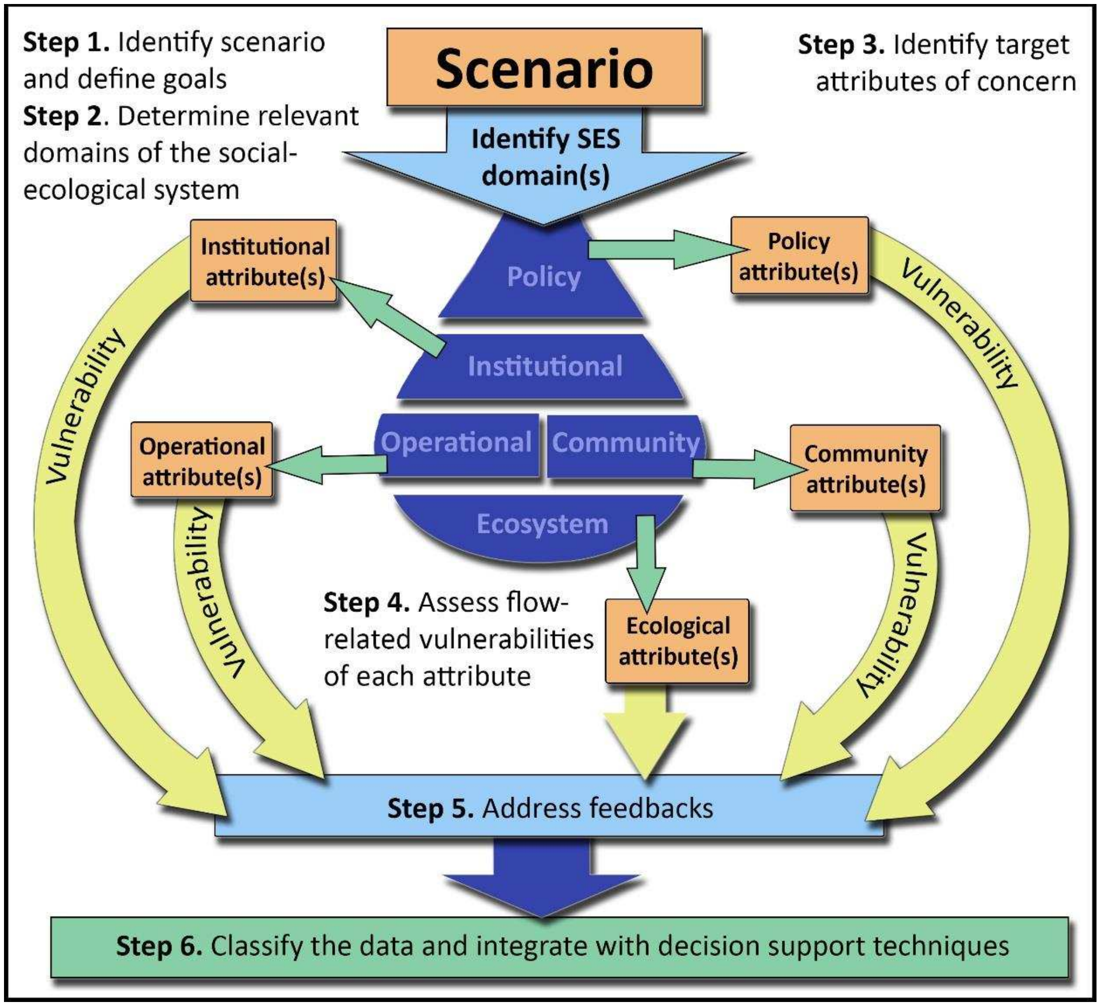

Figure 1.2 Conceptual social-ecological framework to assimilate and evaluate data.

The framework consists of six steps: 1) identify a flow management scenario and define objectives; 2) determine relevant domains of the freshwater SES that are impacted by the flow management scenario; 3) identify target social-ecological attributes from relevant SES domains; 4) assess flow-related vulnerabilities of the attributes through expert opinion and/or data analysis; 5) address feedbacks among system attributes; and 6) classify the data and integrate using decision support techniques.

Steps 1-3 in Figure 1.2 are the data assimilation phase and may be achieved with various stakeholder activities that include but are not limited to: i) focus group meetings to enhance an understanding of the problem and how flow-related data may be effectively used in its analysis; ii) formulate several future climate or management (e.g., water supply) scenarios that may impact the seasonal magnitude and timing of flows; ii) use existing data or perform limited empirical modeling of system components to understand relevant flow-response conditions with respect to the problem scenario(s).

Table 1.2 provides a growing knowledge base on the different kinds of relevant water data that may be useful for future holistic approaches to environmental flows management. We provide data from the current environmental flows literature that can be used as reference information for identifying SES domains and attributes to develop flow-related relationships. We anticipate this field of research to grow and incorporate flow needs for a multitude of management objectives.

Table 1.2 Selected reference data for SES analysis of environmental flows. Each attribute is a manageable performance indicator that corresponds to a domain within the SES from Figure 1.2.

SES Domain	Social-ecological Attributes	Relevant Data	Source
Ecosystem	Hydrological Physical Habitat/Hydraulic Biological	*flow regime estimates and metrics that correspond to biophysical indices (see Table 1.1)*	
Community	Cultural Services -indigenous harvest species	Catch per unit effort	Finn and Jackson (2011)
	Ecosystem Services -recreational fishing	Preference survey estimates of willingness to pay for optimal flow ranges	Daubert and Young (1981)
	-recreational whitewater	Estimated visitor days for optimal flow ranges	Sanderson et al. (2012a)
Operational	City Water Quality Standards	Instream nutrient loading; 14xceedance functions	N/A *(attribute is a suggestion)*
	Agricultural	Percent change of water storage capacity based on instream ecological and policy needs	Grantham et al. (2013)
Institutional	Water Rights	Instream flow availability based on fulfillment of senior water allocations	N/A *(attribute is a suggestion)*
Policy	Threatened and Endangered Species	Instream flow requirements based on federal regulations	Sanderson et al. (2012a)

We consider vulnerability in Step 4 as a function of a flow alteration scenario. We measure vulnerability for each attribute by quantifying flow-related condition estimates. In other words, we construct a relationship between the flow regime and the attribute's condition and use that information to assess the effect of a flow alteration scenario. Expert opinion and/or empirical analyses (e.g., ESWM, DRIFT, ELOHA) may be used to derive condition estimates of the attributes for a scenario. Likewise, empirical results of some attributes may be used alongside alternative data sources that pertain to other relevant attributes. We stress, however, that results of disparate methods may be translated into common currencies (e.g., "Low," "Medium," "High") to enable the simultaneous comparison and evaluation of all attributes. To illustrate, flow-related ecological and socioeconomic data modeling may be used with expert opinion to decompose a vulnerability estimate into exposure, sensitivity, and/or resilience criteria values (Turner et al., 2003) (Table 1.3).

Table 1.3 Example evaluation matrix for scenario planning on a single, hypothetical scenario ("A"). The definitions for vulnerability criteria are uniquely tied to each attribute and intentionally not defined here. Attributes are stakeholder defined and defined in specific metrics and units. Estimates of attribute condition (based on unit data) are translated into a common ordinal scale of criteria values, which are uniquely defined for each attribute. Management priority depends on the decision context. In this example scenario, stakeholders want to prioritize attributes that are most vulnerable ("1") to changes in river flows.

Flow Scenario "A"

Attribute	Expert/Empirical Data		Vulnerability Criteria			Management Priority
	Metrics	**Units**	**Exposure Value *min***	**Sensitivity Value *min***	**Resilience Value *max***	
Native Fish	Discharge (% alteration); wetted perimeter	Seasonal fish abundance	Low	Moderate	Good	4
Recreational Whitewater	Discharge (% alteration)	Seasonal usable days	High	Very Low	Fair	3
City Water Quality	Discharge (% alteration); nutrient loading	Parts per million	High	High	Fair	2
Agriculture	Discharge (% alteration); storage capacity	Square kilometers	Medium	Very High	Poor	1

Step 6 of our framework is performed to integrate attributes under a management decision context. An example decision context can begin by asking: What attributes are worth managing? In the example, the step is performed to prioritize the attributes based on comparing their vulnerabilities under alternative flow scenarios (Table 1.3). This step is similar to the current focus of DRIFT (King and Brown, 2006) and we assert that quantitative methods for multi-criteria decision analysis (MCDA) (Belton and Stewart, 2002) are designed to allow for this integration. MCDA, which combines methods from systems theory and operations research, allows for the assessment of scenarios that have multiple sources and types of attribute data, and addresses feedbacks (Step 5) if strong links can be made among them. We make these recommendations based on challenges from the academic literature to establish a common classification framework to facilitate SES research (Ostrom, 2009) and to blend evolved methods from decision theory with contemporary interdisciplinary research methods like scenario planning and resilience theory (Polasky et al., 2011).

Methods for multi-criteria decision analysis

Suppose that a decision model for MCDA is formulated to prioritize a finite set of management alternatives a_i, each with a finite set of attributes j. The attribute performance value of an alternative is $z_j(a_i)$. These variables are used in an aggregation model (Eq. 1.1). The relative importance of an attribute to the details of the decision problem are either simulated or communicated directly from stakeholders and given a weight w_j. In general, an alternative will outrank others if the weighted sum of aggregated attribute values are higher than the alternatives in comparison (assuming *maximizing* criteria):

$$max \sum_{j=1}^{k} w_j z_j(a_i) \quad (1.1)$$

for attribute $j = 1, \dots, k$, alternatives $i = 1, \dots, m$

The goal of most methods for MCDA is to prioritize or rank the management alternatives to a discrete decision problem with these fundamental characteristics.

Five additive methods for MCDA are reviewed (Table 1.4): i) Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE II) (Brans et al., 1986), ii) Elimination and Choice Expressing The Reality (ELECTRE III) (Roy, 1996), iii) Analytic Hierarchy Process (Saaty, 1990), iv) weighted average method (WAM) (as described in Goicoechea et al., 1982), and v) compromise programming (CP) (Zeleny, 1973).

Table 1.4 Information on the additive models for MCDA

MCDA Technique	Additive Model	Model Definition	Assumptions
PROMETHEE II	Global Preference: $max \sum_{j=1}^{k} w_j A_j(a_i)$ for alternatives *i*; attributes *j=1,…,k*	Aggregation term *A* is the *degree of truth* that one alternative attribute value is *preferred* over other alternatives in paired comparison. The degree of truth is the membership function of a fuzzy set, which is calculated by the distance between attribute values of alternatives in comparison. Alternatives ranked according to the global preference values.	• Transitivity (e.g., $if\ a > b > c, then\ a > c$) • Weights not needed • Compensatory (i.e., poor attribute values compensated by good values)
ELECTRE III	Global Concordance: $max \sum_{j=1}^{k} w_j B_j(a_i)$ for alternatives *i*; attributes *j=1,…,k*	Aggregation term *B* is the *degree of agreement* that one alternative attribute value is *not worse than* other alternatives in comparison. Discordance (i.e., *degree of disagreement*) influences credibility of Concordance value. Alternatives ranked according to distilling two partial rankings from credibility analysis.	• Transitivity ignored • Weights not needed • Non-compensatory
Analytic Hierarchy Process (AHP)	Global Priority: $max \sum_{j=1}^{k} w_j C_j(a_i)$ for alternatives *i*; attributes *j=1,…,k*	Aggregation term C is a result from normalizing a vector of alternatives for each attribute.	• Verbal scale and reciprocal matrices used for subjective attribute • Ratio scale implies the existence of a natural zero (reference point)
Weighted Average Method (WAM)	Combined Value Function: $\max \sum_{j=1}^{k} w_j D_j[z_j(a_i)]$ for alternatives *i*; attributes *j=1,…,k*	Aggregation term *D* is expected value of alternative i.	• Linear utility function: $D_j[z_j(a_i)] = \alpha_j + \beta_j f(a_i)$ • Highly dependent on weights • Assumes monotonicity • Utility independence • Transitive
Compromise Programming (CP)	Preferred Option: $min \sum_{j=1}^{k} w_j^p [E_j(a_i)]^p$ for alternatives *i*; attributes *j=1,…,k*	Aggregation term E is the distance between the observed attribute value and a desired target value: $E_j(a_i) = \frac{\lvert z_j^* - z_j(a_j)\rvert}{\lvert z_j^* - z_j^{**}\rvert}$ where $z_j^* = \max_{1 \le j \le k} z_j(a_i), z_j^{**} = \min_{1 \le j \le k} z_j(a_i)$	• Equal weights assume that geometric distances determine rank among alternatives • Weights skew search for preferred alternatives

PROMETHEE II and ELECTRE III are considered outranking methods. A rank of alternatives is developed by quantifying the strength of the differences (i.e., the distance) between attribute performance values in paired comparisons of alternatives. Scaling effects are eliminated because strength of preference depends on pairwise comparisons among attribute values with the same units. Like most MCDA models in this analysis, weights are used to specify an importance to the attributes and may skew the search of a preferred alternative. It is popular for the aggregation models for each method to use fuzzy logic to simulate imprecision of the data by reducing the intensity of the differences between attribute values. This is done by assigning membership functions to the attribute values (e.g., indifference, linear, Gaussian, stepwise) (Brans et al., 1986) that map to the same dimensionless scale. If preferable, attribute values can be lumped into ranges and/or given subjective values, which are easily translated into fuzzy numbers.

The AHP differs from the outranking methods because it uses ratios to measure preferences between alternative attribute values. In its simplest form with numerical data, normalizing the attribute values over the management alternatives yields a priority vector. This vector is multiplied by the importance weights of each attribute and summed over all attributes to yield a global priority vector. The AHP accommodates subjective attribute values, which are translated from Saaty's verbal scale to a 9-point number scale (Saaty, 1990). Paired judgments between alternative attribute values are entered into a reciprocal matrix and the eigenvalue technique is used to develop a priority vector of the alternatives for this attribute. A consistency indicator is used to reject reciprocal matrices that are logically inconsistent to an established maximum eigenvalue that has been pre-defined based on simulation for the matrix order. This method is unique in that hierarchical information like sub-attributes can be easily included to develop the global priority vector.

The WAM is related to utility function methods (e.g., simple multi-attribute rating technique). They are used to estimate the expected value of an alternative based on transforming information on the attribute tradeoffs into a utility function for each alternative. Utility as a concept maintains a set of axioms, developed from economic theory, that use a different set of assumptions than other MCDA approaches (Belton and Stewart, 2002). Based on the popularity of utility theories, this family of methods is most commonly used.

The CP method is an interactive method for MCDA. It organizes and ranks alternatives according to the closeness of attribute values z_j to target or "ideal" attribute values z_j^*. Closeness is based on using a family of distance metrics p. Popular distance metrics are the absolute value or "Manhatten" norm ($p = 1$), the Euclidean norm ($p = 2$), and the Chebychev or "min-max" norm ($p = \infty$). As $p > 1$, more importance is given to larger distances between the attribute values of an alternative and the target attribute values.

The quest for holistic flow management

The challenge to sustain freshwater ecosystem conditions while satisfying consumptive and non-consumptive uses lies at the complex interface of ecological science and social science. Lasting solutions will require blending ecological theory with social science methods in an open dialogue with collaborations among ecologists, biologists, geomorphologists, economists, watershed planners, and other, non-technical stakeholders. This chapter reviews traditional approaches for making EFRs and highlights the need for a systematic social-ecological systems approach and MCDA techniques to account for and integrate societal objectives for holistic streamflow management. Our framework operationalizes the multi-objective integration needed for sustainable river management.

CHAPTER 2: INCORPORATING SOCIAL PREFERENCES INTO THE ECOLOGICAL LIMITS OF HYDROLOGIC ALTERATION (ELOHA): A CASE STUDY IN THE YAMPA-WHITE RIVER BASIN, COLORADO

Portions of this chapter have appeared in print (Martin et al., 2015)

Summary

River management involves satisfying societal preferences alongside environmental needs for a healthy river ecosystem. Environmental flows is a discipline that aims to define streamflow requirements that achieve desired social and ecological conditions in rivers. The Ecological Limits of Hydrologic Alteration (ELOHA) framework takes a regional approach toward assessing relationships between human-caused river flow alterations and social-ecological benefits. ELOHA allows for, but does not specify, a social process with practical guidelines for incorporating social preferences into environmental flow management problems. Studies using the ELOHA framework are being performed around the world.

This chapter presents development of a decision support tool to prioritize river basin criteria and to rank river segments in order of combined hydro-ecological and social environmental flow needs. We integrate this tool with hydro-ecological components of an ELOHA application in the Yampa-White River basin in northwest Colorado. Stakeholder preferences were collected with a survey and the analytic hierarchy process was applied to estimate the importance of five criteria identified as socially valued proxies of freshwater management in the basin. Analytical methods for multi-criteria decision analysis were used to integrate the preference information with results from the ELOHA application to prioritize the basin river segments. Our methods and results provide a means to facilitate stakeholder negotiation and future environmental flow policy analyses. By extending the existing ELOHA framework to include a social preference

component, this approach is general and can be applied to environmental flow policy and management in other river basins

Introduction

River management involves satisfying societal preferences alongside environmental needs for a healthy river ecosystem. Water supply, recreation, drinking water, flood protection and hydropower have long been societal objectives for river management. Environmental needs have gained importance as they are viewed in the practice of environmental flows, defined in the Brisbane Declaration (2007) as "the quantity, timing, and quality of water flows required to sustain freshwater and estuarine ecosystems and the human livelihoods and well-being that depend on these ecosystems" (http://www.watercentre.org/news/declaration).

The environmental flows concept represents a consensus among river scientists that water supply, water quality and the ecological integrity of rivers are largely influenced by variations in streamflow (Poff et al., 1997; Richter et al., 1997). Environmental flow requirements are estimated by statistically accounting for changes (i.e., alterations) in measurable streamflow quantities and linking these alterations to measured geomorphic and ecological processes. Quantification of flow-ecology relationships (Poff and Zimmerman, 2010) help to operationalize the concept that streamflow is a valuable indicator of a functioning river ecosystem and for biodiversity (Bunn and Arthington, 2002).

Hundreds of methods have been developed to estimate environmental flow requirements for valued ecological indicators of river ecosystems. Most are applied to regulated, single-site systems where human modifications have impacted riverine ecology (Tharme, 2003). The Ecological Limits of Hydrologic Alteration (ELOHA) framework (Poff et al., 2010) takes a regional and multi-site approach toward assessing relationships between human-caused river flow alterations and social-ecological benefits. ELOHA allows for, but does not specify, a social process with practical guidelines for incorporating social preferences into management problems that analyze flow-ecology relationships alongside stakeholder-defined preferences. Studies using the ELOHA framework are being performed around the world (Kendy et al., 2012; Reidy Liermann et al., 2012; McManamay et al., 2013; Mackay et al., 2014; Tavassoli et al., 2014).

The science and management of environmental flows is well-established (see *Freshwater Biology* special issue "Environmental flows: Science and Management," 2010; Arthington, 2012). ELOHA is a widely embraced framework for global environmental flow management yet few publications have explicitly addressed the social process that is embedded in the framework. Finn and Jackson (2011) and Pahl-Wostl et al. (2013) suggest the inclusion of indigenous and governance-based preferences into ELOHA, respectively, but do not develop methods or present case studies for such a process. Where ELOHA has been implemented, setting water management standards is based solely on flow-ecology relationships and do not include social preferences (Kendy et al., 2012). These implementations not only lack social preferences, they lack a formal decision support approach for evaluating social-ecological tradeoffs.

For individual rivers, decision support approaches that have been developed integrate hydro-ecological response models with socioeconomic management needs to systematically design alternative river management options. When used, they are largely applied to a single regulated river system using, e.g., "designer" flow regimes (Acreman et al., 2014). For such site-specific applications, optimization methods are used to design management options that tradeoff ecological targets with water allocation objectives (Homa et al., 2005; Yang, 2011), human sustenance desires (King et al., 2003), and multi-purpose reservoir system objectives (Cardwell et al., 1996; Richter and Thomas, 2007; Barbour et al., 2011; Labadie et al., 2012; Steinschneider et al., 2013; for a review, see Jager and Smith, 2008). The general application of optimization into computerized decision support systems to allocate freshwater from multi-purpose reservoir systems is rich (for reviews, see Labadie and Sullivan, 1986 and Labadie, 2004). Other methods like Bayesian belief networks (Stewart-Koster et al., 2010) offer alternative probabilistic decision support approaches.

Multi-criteria decision analysis (MCDA) is a discipline that uses specific analytical techniques to formally evaluate tradeoffs associated with alternative river management options. MCDA is unique in that different management options with different performance measures and units can be prioritized based on transforming data into a common scale and including social preferences into the tradeoffs analysis. Previous case studies using MCDA to evaluate alternative environmental flow management options include Flug and Ahmed (1990), Hämäläinen et al. (2001), Shiau and Wu (2006), Alexander et al. (2006), Marttunen and Hämäläinen (2008), King and Brown (2010), Barton et al. (2010) and Beilfuss and Brown (2010).

This chapter has two specific aims: to develop a social process that extends ELOHA beyond solely hydro-ecological principles and to a more complete decision making framework, and to use MCDA to evaluate tradeoffs among social preferences and ecological needs in a multi-site, whole river basin. We developed a decision support tool to prioritize river basin criteria and to rank river segments in order of combined hydro-ecological and social environmental flow needs. For a case study, we complement a published application of ELOHA on the Yampa-White River basin in northwest Colorado. That application quantified hydro-ecological relationships and flows required to maintain biological, recreational, and policy criteria at river segments throughout the basin. The decision support tool was developed to elicit preference information from stakeholders in the basin and implement a formal MCDA evaluation of the basin river segments as proxies of future flow management policy options.

Methods

Study basin and relevant social-ecological data

The Yampa and White Rivers flow in a westerly direction in Colorado toward the Green River, a major tributary to the Colorado River (Figure. 2.1). The catchments, hereafter referred to as the basin, cover lands mostly in the public domain that are managed by federal agencies. Socioeconomic beneficiaries in the basin are from the agriculture and tourist (e.g., fishing, boating and skiing) sectors. Portions of the tourist sector have a social preference to maintain environmental flows for ecosystem service benefits (e.g., trout fisheries, recreational whitewater).

The Colorado Water for the 21st Century Act (House Bill 2005-1177) called for the negotiation of water resource management in locally-driven collaborative decision contexts. To facilitate this objective, "basin roundtables" were created as groups of citizen stakeholders who reside inside the boundaries of each of the nine river basins in Colorado. As part of the multi-basin non-consumptive freshwater needs assessment, the Yampa-White River basin roundtable sponsored The Nature Conservancy to perform an ELOHA application called the Yampa-White Basin Roundtable Watershed Flow Evaluation Tool Study (WFET) (Sanderson et al., 2012a; https://www.conservationgateway.org/Files/Pages/yampawhitewfet.aspx).

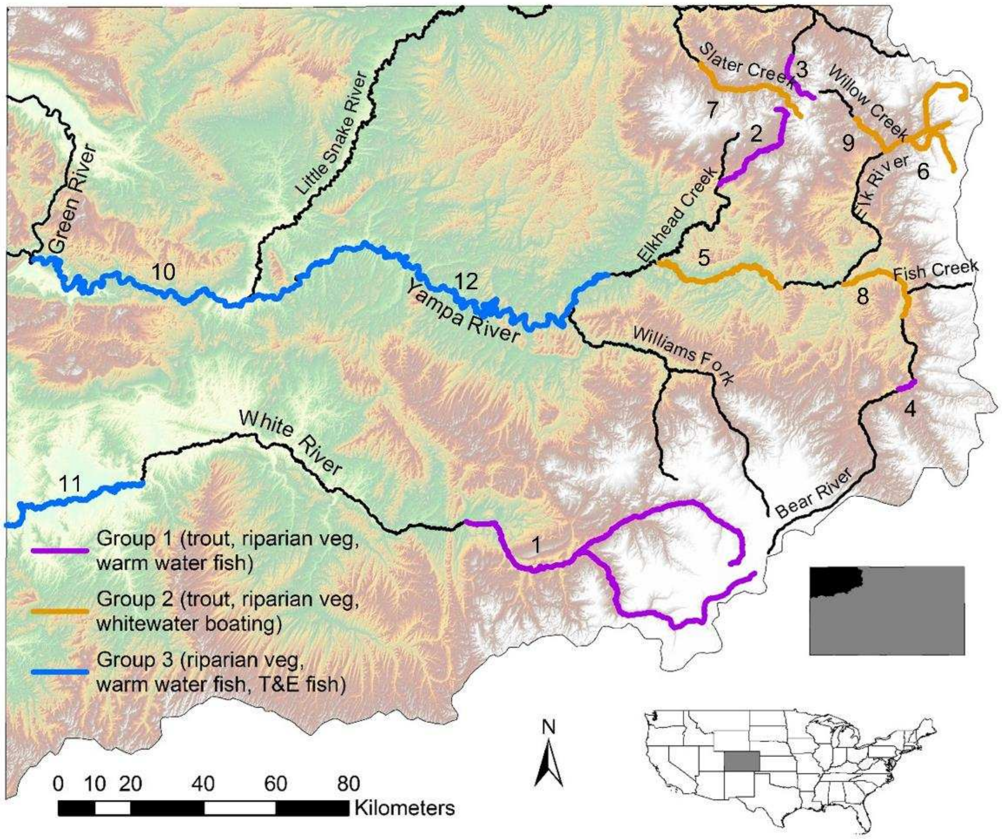

Figure 2.1 Yampa-White River basin map with approximate river segment locations numbered. The river segments are partitioned into groups with the same criteria.

The WFET used practical guidelines from the ELOHA framework to assess current flow-based conditions of social-ecological criteria at 12 pre-determined river segments throughout the basin. Three biological criteria were identified by the basin roundtable as valued sustainability measures to the basin and include trout fish (cutthroat, brook, brown, rainbow), riparian vegetation (native cottonwood) and warm water fish (bluehead sucker, flannelmouth sucker, roundtail chub). Two additional flow-based criteria were included in the ELOHA application: recreational whitewater boating opportunities and threatened and endangered (T&E) fish (Colorado pikeminnow, humpback chub, bonytail chub, razorback sucker).

To summarize the initial phases of the ELOHA application, a basin-wide hydrological model contrasted baseline and developed river flows at instream flow monitoring locations, which were used to distinguish the 12 basin river segments (Figure. 2.1). The classification was performed to develop metrics appropriate for quantifying streamflow requirements for the trout, riparian vegetation and warm water fish criteria. The Indicators of Hydrologic Alteration method (Richter et al., 1996) and accompanying software were used to estimate ecologically important streamflow metrics describing baseline and developed river flow conditions at the river segments.

Flow-ecology relationships for the biological criteria were established based on an extensive literature review and expert opinion case study for sites throughout the state of Colorado (see Sanderson et al., 2012b). The risk of deteriorating trout populations, riparian vegetation populations and warm water fish biomass was estimated by establishing different probability-based impairment classifications for these criteria. These were based on quantifying the relationship between percent reductions in criteria metrics with flow modifications. In addition to estimating flow-ecology relationships of the biological criteria, preferred river flows for recreational whitewater boating were developed based on an American Whitewater recreation survey and geographic analysis (Sanderson et al., 2012a). Lastly, designation of suitable flows for T&E fish were based on recommendations in the U.S. Fish and Wildlife Service's Programmatic Biological Opinion (PBO) (USFWS, 2005) and related documentation.

Following quantitative analyses, expert opinion was used to assign a common linguistic classification of degrees of impairment to the five basin criteria, hereafter *impairment classes*, which represent the current flow-based status of each criterion at the basin river segments. A summary of the flow-related metrics and impairment classifications for each criterion is given in Table 2.1. The classification uses common terminology but impairment classes are not comparable across basin criteria because different quantitative flow-based metrics and methods were used to determine different degrees of impairment.

Table 2.1 Information used to estimate impairment classes of criteria in the Yampa-White River basin (*Source:* Sanderson et al., 2012a). The linguistic classifications for each criterion were transformed into sets of ordinal fuzzy numbers for the decision analysis

Basin criteria	Flow metric(s) (cubic feet per second)	Flow-based relationship	Impairment class	Fuzzy number
Trout	Mean annual Flow (MAF) Mean August flow Mean September flow	Summer low flows <10% MAF	Very High	5
		Summer low flows 10-15% MAF	High	4
		Summer low flows 16-25% MAF	Moderate	3
		Summer low flows 26-55% MAF	Minimal	2
		Summer low flows >55% MAF	Low	1
Riparian Vegetation	Mean annual peak daily flow 90-day maximum flow (wet years)	Dependent on geomorphic setting (confined vs. unconfined); links to a percent range of flow alteration (different for each river segment)	Very High	4
			High	3
			Moderate	2
			Low	1
Whitewater Boating	Segment-specific flow ranges	Current streamflow ranges suitable for recreational usable days (different for each river segment)	High	3
			Moderate	2
			Low	1
Warm Water Fish	30-day low flow (July through November)	25-50% reduction in potential biomass	High	3
		10-15% reduction in potential biomass	Moderate	2
		<10% reduction in potential biomass	Low	1
T&E fish	U.S. Fish and Wildlife Service Programmatic Biological Opinion	Current streamflow < recommendation	High	2
		Current streamflow ≥ recommendation	Low	1

Preceding the completion of the WFET study, we participated in discussions with volunteer basin roundtable members to establish a working relationship and elicit ideas on how the results could be incorporated into a decision making policy context. The group decided to target basin river segments that have the highest needs for environmental flow management, i.e., river segments with high flow-based impairment. Based on this input and data available in the WFET, a decision analysis process (Figure. 2.2) and electronic support tool was designed to prioritize basin river segments. Following stakeholder-defined preferences, river segments that were prioritized by the tool are considered highly impaired and require environmental flow management. The decision analysis process required two components: assigning stakeholder-assigned importance (i.e., weighting factors) to the five basin criteria, and integrating the criteria weighting factors into a prioritization of the river segments using the published WFET data.

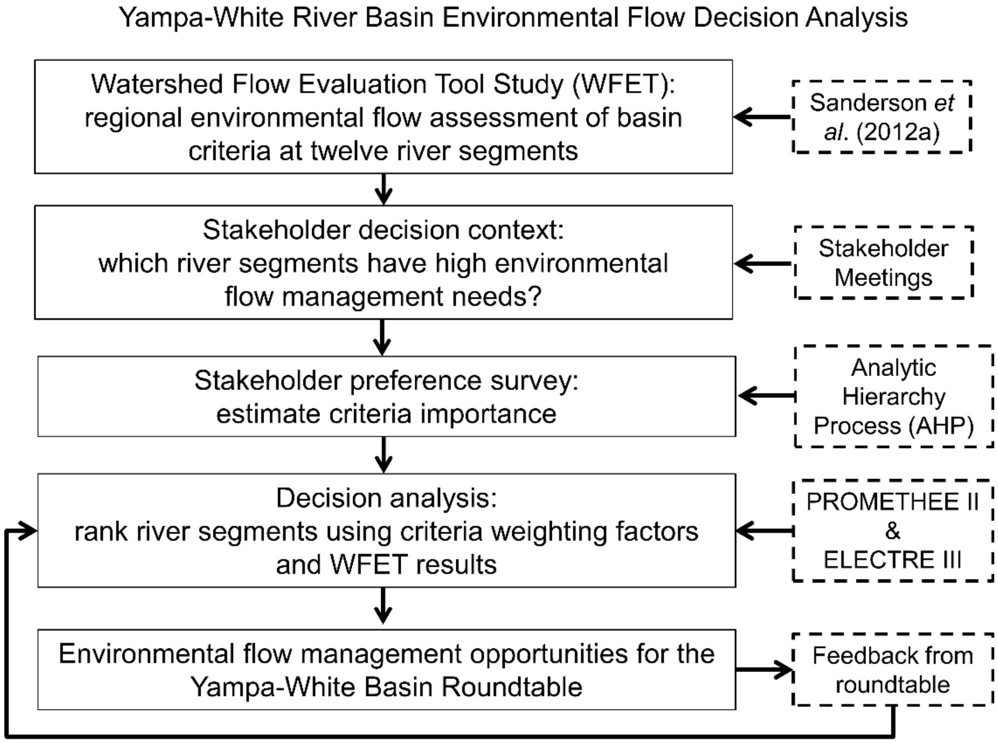

Figure 2.2 A conceptual flow chart for the decision analysis.

Prior to proceeding with the decision analysis, a common currency was needed for comparing the river segments with MCDA methods. To do this, impairment classes for each criterion were transformed into sets of fuzzy numbers ("fuzzy sets"; Zadeh, 1965) that represent an impairment score (right-hand column in Table 2.1). The assignment of fuzzy numbers is to generalize the order of impairment classes for analytical comparison using MCDA. Fuzzy numbers are arbitrary so long as they maintain ordinal scales in succession and correspond to stakeholder-defined preferences for comparing impairment classes in the decision analysis. Based on this and the objective to prioritize impaired river segments, highly impaired classes were given higher fuzzy numbers.

The 12 river segments were divided into three groups where each group of river segments included the same three criteria (Figure. 2.1): Group 1 are river segments that estimated impairment class values for the trout, riparian vegetation and warm water fish criteria, Group 2 are segments that estimated values for the trout, riparian vegetation and whitewater boating criteria and Group 3 are segments that estimated values for the riparian vegetation, warm water fish and T&E fish criteria. The current flow-based impairment status for each criterion at each river segment was taken from Sanderson et al. (2012a) and transformed into a corresponding fuzzy number. This information was used to populate an analytical evaluation table for each river segment group (Table 2.2).

Table 2.2 Evaluation table for using MCDA to compare river segments within each basin group. The fuzzy numbers correspond to a current impairment status for each basin criteria (see **Table 2.1**)

Group 1	Trout	Riparian Vegetation	Warm Water Fish
Segment 1	1	2	1
Segment 2	5	1	3
Segment 3	4	1	1
Segment 4	1	4	1
Group 2	Trout	Riparian Vegetation	Whitewater Boating
Segment 5	3	2	2
Segment 6	2	1	1
Segment 7	4	1	3
Segment 8	3	2	1
Segment 9	2	1	3
Group 3	T&E Fish	Riparian Vegetation	Warm Water Fish
Segment 10	1	2	2
Segment 11	1	2	1
Segment 12	1	2	1

Method to estimate basin criteria weights

Following development of the decision analysis process (Figure. 2.2), we estimated a priority vector of weighting factors for the basin criteria using the analytic hierarchy process (AHP) (Saaty, 1990) method. AHP breaks down a decision problem into a hierarchical structure that aids in the comparison of all pairs of elements within the $n - 1$ levels of the structure. A three-level objectives hierarchy was developed to aid in estimating criteria importance with AHP (Figure. 2.3). The overall objective focuses on non-consumptive freshwater uses (i.e., species conservation and ecosystem services). The sub-objectives contribute to achieving the overall objective in different ways and were defined after the Environmental Protection Agency's pillars of sustainability (epa.gov/ncer/rfa/forms/sustainability_primer_v7.pdf). The five basin criteria are at the lowest level of the hierarchy.

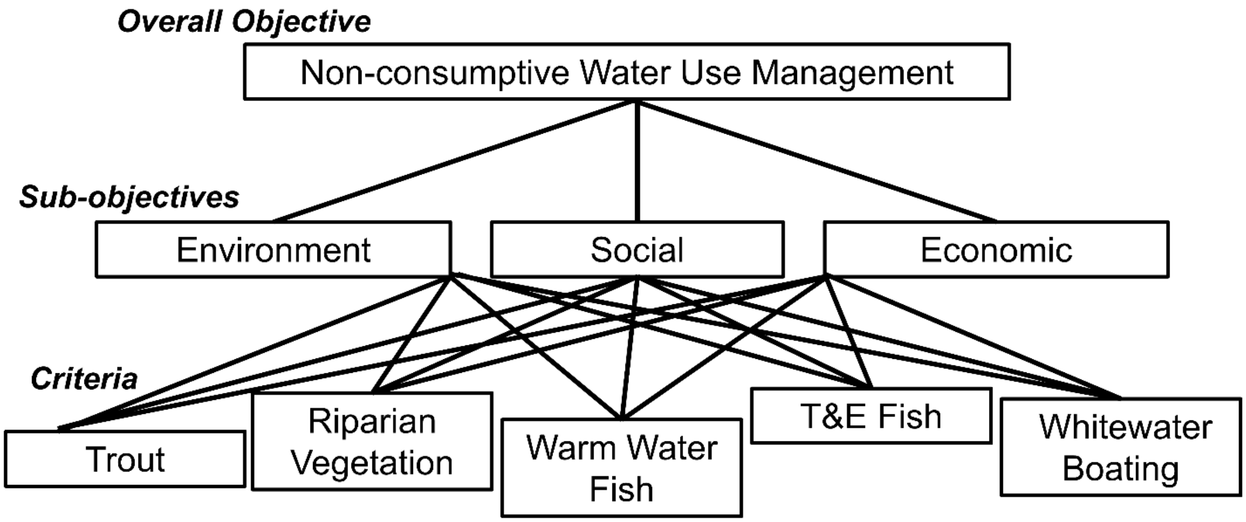

Figure 2.3 A three-level objectives hierarchy was used to design a stakeholder preference survey that estimated basin criteria weights with the analytic hierarchy process.

To calculate a priority vector of criteria weights with AHP, preference judgments are produced for each pair of elements on one hierarchical level with respect to elements at the upper adjacent hierarchical level. Each paired judgment corresponds to Saaty's verbal scale (Saaty, 1990) and measures the intensity of importance of one element over another in paired comparison. For example, a verbal judgment of "equal importance" means that two compared sub-objectives like the environment and economy are equally meaningful to achieve the overall objective. Likewise, judgments of "moderate importance" mean that experience slightly favors one criterion over another. Saaty's verbal scale also includes judgments of "strong importance", "very strong importance" and "extreme importance" with related linguistic meanings.

Verbal preference judgments made using the AHP method correspond to Saaty's ordinal number scale (Saaty, 1990). The translation of verbal judgments to numerical values allows them to be entered into an analytical reciprocal matrix for each $n-1$ levels of the objectives hierarchy. The eigenvalue technique analyzes each reciprocal matrix to converge to a vector of weights that corresponds to the elements on the sub-objectives and criteria levels of the hierarchy. In brief, a priority vector of weights (w) is computed as the principle right eigenvector of the reciprocal matrix (A) of numerical judgment values (a_{ij}):

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}, a_{ij} = \frac{1}{a_{ji}} \tag{2.2 }$$

$$w = \lim_{n \to \infty} \frac{A^k e}{e^T A^k e}, e = unit\ vector \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \tag{2.3 }$$

The maximum eigenvalue (λ_{max}) is calculated by selecting a row i of the A matrix:

$$\lambda_{max} = \frac{\sum_{j=1}^{k} a_{ij} w_j}{w_i} \quad (2.4)$$

where w_j is the i^{th} position in the eigenvector.

Stakeholder preference survey

Stakeholder preferences of the 11-member non-consumptive needs sub-committee of the basin roundtable were elicited in a survey from May to August, 2013. The sub-committee was non-randomly chosen for the preference survey because they reflected a local context for water use management in the basin. The surveys were distributed through email in Microsoft PowerPoint and Microsoft Word formats to all members of the sub-committee. Included in the survey was background information on the criteria that were evaluated in the published WFET study as well as definitions for each sub-objective. To define the environment sub-objective, the terms “ecosystem services”, “air quality”, “water quality” and “waste management” were used. Likewise, the terms “human health”, “education” and “sustainable communities” were given to define the social sub-objective and “jobs”, “supply and demand” and “natural resource accounting in cost benefit analyses” were given to define the economic sub-objective. In general, we wanted all respondents to approach the AHP questions with common background knowledge and terminology.

The survey then elicited stakeholder judgments about the strength of importance for each sub-objective and criterion of the hierarchy (Figure 2.3) based on pairwise comparisons of same-level elements using AHP questions and Saaty’s verbal scale. AHP questions pertaining to sub-objectives took the form: “Which of the following objectives are more important with respect to the overall goal of sustainable non-consumptive freshwater use management in the Yampa-White Basin?” Questions for criteria took the form: “Which of the following criteria are more important with respect to the *social/economic/environment* objective in the Yampa-White

Basin?" In total, a single respondent was asked to make three paired judgments on the sub-objectives and 30 paired judgments on the basin criteria. Two types of surveys were randomly delivered to the individuals with alternative ordering of criteria given in the AHP questions. The biocentric and anthropocentric types of criteria ordering was done as indirect controls for bias (e.g., Tversky & Kahneman, 1973) to the words that came first and more frequently in the pairwise comparisons.

Seven (out of 11) surveys were returned and given unique identification numbers to hold the responders' identity confidential. The qualitative judgments of the seven respondents were translated into Saaty's number scale (Saaty, 1990) and used to populate reciprocal matrices in a Microsoft Excel spreadsheet. According to the Alonso and Lamata (2006) method, λ_{max} is the measure of a consistency index and varies according to a designated value of the error called a consistency error, α, and with matrix order. We allowed for a slightly higher degree of inconsistency, $\alpha = 0.15$, than Saaty's (1990) original acceptance method, which corresponds to $\alpha = 0.10$. This choice was made because the stakeholder group represents an array of disciplines and there is a potential unfamiliarity with semantic scoring techniques. In other words, we wanted to allow more flexibility in accepting their preference judgments.

Since the environmental flow decision analysis is based on three groups of river segments that evaluate the same criteria, three 5^{th} order matrices of group (i.e., geometric mean) judgments of the criteria per sub-objective were used to generate a single 3^{rd} order matrix of criteria weights for each river segment group. Figure 2.4 explains the steps for developing the criteria weights for Group 2 river segments using calculations from the stakeholder group survey responses. Matrix multiplication of criteria weights was applied with the sub-objective weights to generate overall priority weights in each river segment group (Figure. 2.4, panel d).

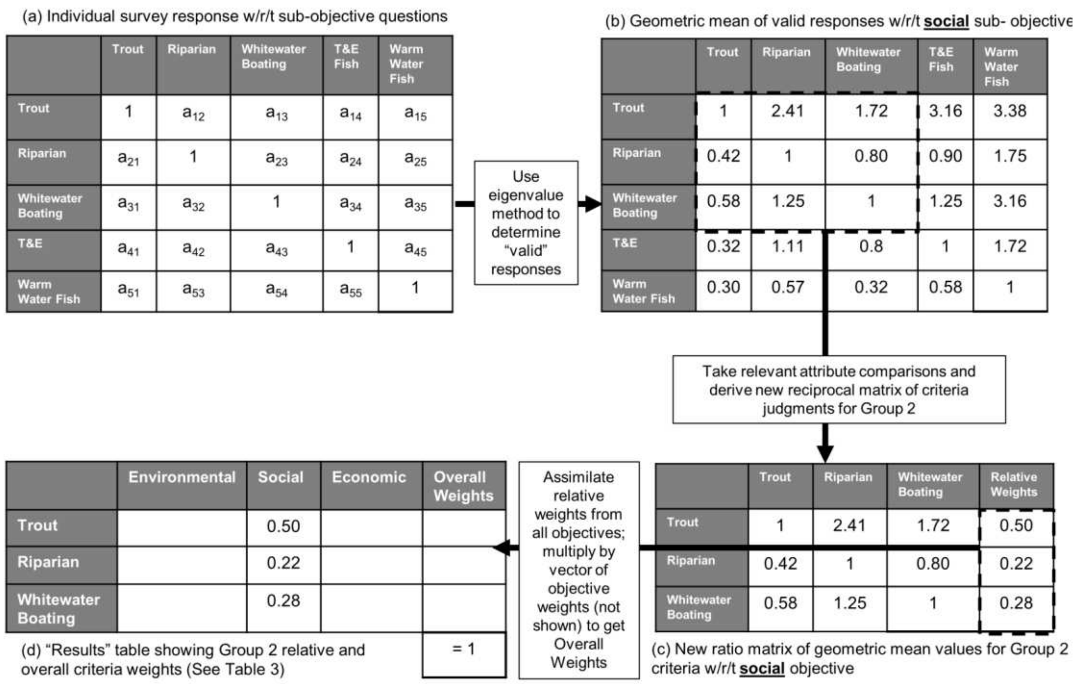

Figure 2.4 Explanation of steps taken for calculating overall weights for Group 2 basin criteria. We developed separate 5th order reciprocal matrices that compared the criteria with respect to each sub-objective. Shown in panel (a) is a generic matrix that we developed for each respondent per sub-objective. After accounting for logical consistency of respondent answers (i.e., eigenvalue technique), the geometric mean of the valid responders' judgments were extracted for all criteria judgments with respect to each sub-objective. Panel (b) shows the geometric mean of the group responses with respect to paired comparison questions pertaining to the "social" sub-objective. In panel (c), a reciprocal matrix of relevant geometric mean values was developed to correspond to criteria comparisons per sub-objective that were specific to Group 2 river segments. Recall that Group 2 river segments modeled for trout, riparian vegetation, and whitewater boating opportunities (Figure. 2.1). We aggregated relative weights over all sub-objectives (not shown) using matrix multiplication to generate overall weights in panel (d).

Methods to prioritize basin river segments

Outranking methods were used to rank river segments by integrating the Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE) (Brans et al., 1986) and ELimination and Choice Expressing The REality (ELECTRE) (Roy, 1996) methods with published criteria risk data from Sanderson et al. (2012a). With these methods, a ranking of the river segments is derived by quantifying the strength of the differences between criteria impairment condition estimates between pairs of river segments. PROMETHEE II and ELECTRE III are applied to assign complete rankings of river segments that support stakeholder management priorities in the Yampa-White Basin.

Outranking relationships are quantified in PROMETHEE II with a fuzzy membership function, defined as the degree of truth that one river segment outranks another by comparing their criteria condition estimates in pairs. There are a number of fuzzy membership functions (e.g., indifference, linear, Gaussian) (Brans et al., 1986) that map to the same dimensionless scale (0-1) where values closer to one offer stronger support of an outranking relationship between two alternative river segments. This idea was translated to how the basin roundtable members may be "fuzzy" in their certainty for the criteria condition estimates from Sanderson et al. (2012a).

In PROMETHEE II, a global preference index (π) is the weighted (w_j) vector sum of membership function values (P_j) where one river segment (a_1) outranks another (a_2) over all j criteria:

$$\pi(a_1, a_2) = \sum_{i=1}^{j} w_j P_j(a_1, a_2) \tag{2.5}$$

This preference index is used to identify positive outranking flow (ϕ^+) and negative outranking flow (ϕ^-) and quantifies the extent that a river segment (a_i) outranks all others (x) and is outranked by all others, respectively:

$$\phi^+(a_i) = \sum \pi(a_i, x) \quad (2.6\ )$$

$$\phi^-(a_i) = \sum \pi(x, a_i) \quad (2.7\ )$$

A complete ranking relationship is developed by ordering the net outranking flow over all alternatives ($\phi(a_i)$).

$$\phi(a_i) = \phi^+(a_i) - \phi^-(a_i) \quad (2.8\ )$$

Like PROMETHEE II, ELECTRE III methods are based on the strengths of the differences between criteria condition estimates for comparing pairs of river segments. Several indices are produced in ELECTRE III that validate a complete rank among alternatives (Roy, 1996) and map to a similar dimensionless scale. Concordance $c_j(a_1, a_2)$ is defined as the degree of agreement that one river segment impairment class estimate $f_j(a_1)$ is not worse off than the other $f_j(a_2)$. Likewise, discordance $d_j(a_1, a_2)$ is defined as the degree of disagreement that one river segment impairment class is not worse off than the other:

$$c_j(a_1, a_2) = \begin{cases} 1 & if\ f_j(a_1) + q_j \geq f_j(a_2) \\ 0 & if\ f_j(a_1) + p_j \leq f_j(a_2) \\ \frac{p_j + f_j(a_1) - f_j(a_2)}{p_j - q_j} & otherwise \end{cases} \quad (2.9\ )$$

$$d_j(a_1, a_2) = \begin{cases} 0 & if\ f_j(a_1) + p_j \geq f_j(a_2) \\ 1 & if\ f_j(a_1) + v_j \leq f_j(a_2) \\ \frac{f_j(a_2) - f_j(a_1) - p_j}{v_j - p_j} & otherwise \end{cases} \quad (2.10\ )$$

Relationships of concordance and discordance are used to simulate imprecision within a decision space. For concordance, a "zone of hesitation" between impairment class parameters (p_j) and (q_j) represents a descending linear relationship between strict preference and indifference. Likewise, the discordance region is between a distance parameter (p_j) and a "veto threshold" (v_j) (Roy, 1996). With these indices, global concordance $c(a_1, a_2)$ is defined as the sum of weighted concordances for all pairs of river segments, normalized by the sums of the weights:

$$c(a_1, a_2) = \frac{\sum_{j=1}^{m} w_j c_j(a_1, a_2)}{\sum_{j=1}^{m} w_j} \tag{2.11 }$$

Although the ELECTRE indices were developed apart from fuzzy set theory, they are considered useful in developing insensitive, indifference and linear fuzzy relationships (Figueira et al., 2005), which is reflective in the concordance value. To integrate discordance, a credibility matrix is developed that includes values $S(a_1, a_2)$ for all possible pairwise comparisons:

$$S(a_1, a_2) = \begin{cases} c(a_1, a_2)\ if\ d_j(a_1, a_2) \leq c(a_1, a_2) \forall j \\ \quad or: c(a_1, a_2) \prod_{j \in J(a_1, a_2)} \frac{1 - d_j(a_1, a_2)}{1 - c(a_1, a_2)} \end{cases} \tag{2.12 }$$

where $J(a_1, a_2)$ is the set of criteria such that $d_j(a_1, a_2) > c(a_1, a_2)$. If there are degrees of discordance associated with a comparison, then the "credibility" of the relationship is reduced by impacting the concordance value. This is an important non-compensatory assumption for ELECTRE III that is absent in PROMETHEE II.

To develop a ranking with ELECTRE III, two partial rankings from the credibility scores are used in a descending (i.e., best to worst) and ascending (i.e., worst to best) distillation process. After the first step is performed in each distillation, the highest ranked (i.e., "credible") river segment (descending) or lowest ranked river segment (ascending) is removed and the problem is re-evaluated with $n - 1$ river segments until all partial orders have been defined. A final rank can be made for the distillation process via averaging the two partial rankings.

Sensitivity Analysis

A sensitivity analysis procedure was designed to yield several sets of river segment rankings within each basin group. The analysis was based on iterations of PROMETHEE II and ELECTRE III using different combinations of fuzzy criteria relationships and the AHP criteria weights (Table 2.3). These iterations were conceived with volunteer basin roundtable member interaction and by conducting a qualitative assessment of the AHP results and were carried out in the Microsoft Excel spreadsheet that was designed for the project.

Table 2.3 Explanation of sensitivity iterations for river segment comparisons using PROMETHEE II and ELECTRE III

Group 1	Weighting factors	Fuzzy criteria relationships	Comments
Iteration 1-1	Equal	None	Simulates no stakeholder preferences; no flexibility between criterion values
Iteration 1-2	AHP Results	Trout: strict Riparian Veg: linear Warm Water Fish: indifferent	Trout: AHP results in highest priority; no flexibility between criterion values Riparian Veg: stakeholder fuzzy "weak" preference between adjacent criterion values (membership & concordance functions = 0.5) Warm Water Fish: AHP results in lowest priority; all segments given same preference
Iteration 1-3	AHP Results	Trout: linear Riparian Veg: strict Warm Water Fish: indifferent	Trout: stakeholder fuzzy "weak" preference between adjacent criterion values (membership & concordance functions = 0.5) Riparian Veg: stakeholders consider criterion a driver of instream health; no flexibility between criterion values Warm Water Fish: AHP results in lowest priority; all segments given same preference
Iteration 1-4	AHP Results	Trout: linear Riparian Veg: indifferent Warm Water Fish: strict	Trout: stakeholder fuzzy "weak" preference between adjacent criterion values (membership & concordance functions = 0.5) Riparian Veg: stakeholders consider criterion a driver of instream health; no flexibility between criterion values Warm Water Fish: no flexibility between criterion values
Iteration 1-5	AHP Results	Trout: indifferent Riparian Veg: linear Warm Water Fish: indifferent	Trout: no preference between adjacent criterion values Riparian Veg: stakeholder fuzzy "weak" preference between adjacent criterion values (membership & concordance functions = 0.5) Warm Water Fish: AHP results in lowest priority; all segments given same preference

Group 2	**Weighting factors**	**Fuzzy criteria relationships**	**Comments**
Iteration 2-1	Equal	None	Simulates no stakeholder preferences; no flexibility between criterion values
Iteration 2-2	AHP Results	Trout: strict Riparian Veg: linear Whitewater Boating: indifferent	Trout: AHP results in highest priority; no flexibility between criterion values Riparian Veg: stakeholder fuzzy “weak” preference between adjacent criterion values (membership & concordance functions = 0.5) Whitewater Boating: AHP results in lowest priority; all segments given same value
Iteration 2-3	AHP Results	Trout: strict Riparian Veg: strict Whitewater Boating: indifferent	Trout: AHP results in highest priority; no flexibility between criterion values Riparian Veg: stakeholders consider criterion a driver of instream health; no flexibility between criterion values Whitewater Boating: AHP results in lowest priority; adjacent criterion values given same preference
Iteration 2-4	AHP Results	Trout: linear Riparian Veg: strict Whitewater Boating: linear	Trout: stakeholder fuzzy “weak” preference between adjacent criterion values (membership function = 0.5) Riparian Veg: stakeholders consider criterion a driver of instream health; no flexibility between criterion values Whitewater Boating: stakeholder fuzzy “weak” preference between adjacent criterion values (membership & concordance functions = 0.5)
Iteration 2-5	AHP Results	Trout: linear Riparian Veg: linear Whitewater Boating: linear	All criteria: stakeholder fuzzy “weak” preference between adjacent criterion values (membership & concordance functions = 0.5)

Group 3	Weighting factors	Fuzzy criteria relationships	Comments
Iteration 3-1	Equal	None	Simulates no stakeholder preferences; no flexibility between criterion values
Iteration 3-2	AHP Results	Riparian Veg: indifference Warm Water Fish: linear T&E Fish: indifference	Riparian Veg: data were the same Warm Water Fish: stakeholder fuzzy “weak” preference between adjacent criterion values (membership & concordance functions = 0.5) T&E Fish: data were the same
Iteration 3-3	AHP Results	Riparian Veg: indifference Warm Water Fish: strict T&E Fish: indifference	Riparian Veg: data were the same Warm Water Fish: illustration to show that fuzziness and AHP weights didn’t matter T&E Fish: data were the same

The first sensitivity iteration for each basin group was performed using equal criteria weights and no fuzzy relationships for the fuzzy numbers being compared. This simulated a situation where no stakeholder preferences are incorporated in the decision analysis. Subsequent iterations integrated the AHP criteria weights with three fuzzy criteria relationships (e.g., indifference, strict preference, linear) that simulated stakeholder imprecisions about the current impairment classes of the criteria within each basin group. Indifference fuzzy relationships signify flexibility in certainty that adjacent fuzzy numbers (i.e., successive impairment classes) are equally preferable (e.g., there is no clear preference between “high” and “moderate” trout classes). Strict preference means that a distinct ranking exists if fuzzy numbers differ (e.g., a membership function equal to unity is assigned for a comparison between “high” and “moderate” trout classes). Linear fuzzy relationships mean that adjacent impairment classes maintain positive but not strict preference (e.g., a “high” trout impairment class positively but does not strictly rank higher than a “moderate” class; fuzzy membership values were equal to 0.5 for this relationship).

In total, five sensitivity iterations of each MCDA method were performed on basin Groups 1 and 2. Three sensitivity iterations of the methods were performed on basin Group 3 because only three river segments were compared and criteria impairment was similar across the segments.

Results and discussion

Basin criteria weights

The preference survey yielded the following AHP results. Sub-objective weights and criteria weights are given in Table 2.4. The results show that the environmental objective was clearly the most valued among the stakeholder group (weight = 0.54) with respect to the overall objective of non-consumptive water use management in the basin. For criteria, trout was the most valued in basin Groups 1 and 2, whereas T&E fish was the most valued in Group 3. Sub-objective priorities among the criteria were consistent with this ordering, with the exception that riparian vegetation was found to be a slightly more valued criterion with respect to the environmental sub-objective in Group 2. As a control measure, we calculated the frequencies of answers to each survey type (biocentric versus anthropocentric) and concluded that individual respondent criteria weights did not relate to the sequencing of criteria in the preference survey.

Table 2.4 Criteria weights for each sub-objective and for each criterion per basin group. Weights in bold are the highest in their respective basin group (see **Figure 2.1**). Columns within each group sum to unity (1).

	Basin criteria	Environment (0.54)	Social (0.18)	Economic (0.28)	Overall Weights
Group 1	Trout	**0.42**	**0.58**	**0.62**	**0.50**
	Riparian Vegetation	0.37	0.26	0.21	0.31
	Warm Water Fish	0.21	0.16	0.17	0.19
Group 2	Trout	0.38	**0.50**	**0.52**	**0.44**
	Riparian Vegetation	**0.40**	0.22	0.20	0.31
	Whitewater Boating	0.22	0.28	0.28	0.25
Group 3	Riparian Vegetation	0.27	0.38	0.35	0.31
	Warm Water Fish	0.15	0.22	0.28	0.20
	T&E Fish	**0.58**	**0.40**	**0.37**	**0.49**

The AHP weights indicate that the environmental sub-objective has a higher priority than social or economic sub-objectives to the stakeholder group as it is perceived for non-consumptive freshwater management in the basin. Trout was the most valued criterion for Groups 1 and 2 and T&E species for Group 3. "Trout" is a collective term from the basin roundtable's perspective and includes endangered as well as introduced species for recreation. Trout are highly valued by upper-basin conservation and recreation beneficiaries. Based on *a posteriori* conversations with volunteer roundtable members, trout as an indicator of non-consumptive basin needs is understandably more important than most other indicators. To quote a roundtable member, the fact that trout was prioritized "makes management sense" because it is highly preferred from tourist beneficiaries in the more populated upper basin.

The designation that T&E fish are prioritized in Group 3, which comprise of downstream basin river segments, also makes sense to the stakeholders. In the lower basin, recreation is largely substituted with agriculture as a dominant beneficiary from the river and this type of freshwater use can significantly alter the river streamflow regimes and subsequently impact sensitive species in the lower basin. In addition, T&E fish are a national priority, which elevates their social perspective and priority.

It is apparent that the survey respondents could establish a clear judgment among basin-wide objectives and criteria. This is noticeable, for example, with the riparian vegetation criterion that varies in weight among the sub-objectives in Table 2.4. This is evident even though there is a clear trend in the highly prioritized criterion (trout) from each group across most sub-objectives.

River segment priorities

The sensitivity analysis yielded different ranks of river segments within each basin group (Tables 2.5-2.7). Table 4 gives the average over all sensitivity iterations for each basin group and shows that river Segments 2, 7, and 10 received the highest priority in the respective groupings (Figure. 2.1). High rank indicates river segments with high environmental flow needs (i.e., river segments with highly impaired criteria).

Table 2.5 Group 1 river segment rankings

Group 1		Iteration 1-1	Iteration 1-2	Iteration 1-3	Iteration 1-4	Iteration 1-5	**Overall Rank**
PROMETHEE II	Segment 1	Tied: 3rd	4th	4th	4th	4th	**4th**
	Segment 2	1st	1st	1st	1st	1st	**1st**
	Segment 3	Tied: 3rd	2nd	2nd	2nd	2nd	**2nd**
	Segment 4	2nd	3rd	3rd	3rd	3rd	**3rd**
ELECTRE III	Segment 1	Tie: 2nd	3rd	4th	4th	2nd	**4th**
	Segment 2	Tie: 1st	1st	1st	1st	Tie: 1st	**1st**
	Segment 3	Tie: 2nd	Tie: 2nd	2nd	2nd	Tie: 1st	**2nd**
	Segment 4	Tie: 1st	Tie: 2nd	3rd	3rd	Tie: 1st	**3rd**

Table 2.6 Group 2 river segment rankings

	Group 2	Iteration 2-1	Iteration 2-2	Iteration 2-3	Iteration 2-4	Iteration 2-5	Overall Rank
PROMETHEE II	Segment 5	Tie: 1st	Tie: 2nd	1st	2nd	Tie: 2nd	**2nd**
	Segment 6	4th	Tie: 3rd	5th	5th	Tie: 3rd	**5th**
	Segment 7	Tie: 1st	1st	2nd	1st	1st	**1st**
	Segment 8	2nd	Tie: 2nd	3rd	3rd	Tie: 2nd	**3rd**
	Segment 9	3rd	Tie: 3rd	4th	4th	Tie: 3rd	**4th**
ELECTRE III	Segment 5	1st	3rd	2nd	Tie: 1st	Tie: 2nd	**2nd**
	Segment 6	4th	Tie: 4th	5th	4th	4th	**5th**
	Segment 7	Tie: 2nd	1st	1st	Tie: 1st	1st	**1st**
	Segment 8	Tie: 2nd	2nd	3rd	2nd	Tie: 2nd	**3rd**
	Segment 9	3rd	Tie: 4th	4th	3rd	3rd	**4th**

Table 2.7 Group 3 river segment rankings

	Group 3	Iteration 3-1	Iteration 3-2	Iteration 3-3	Overall Rank
PROMETHEE II & ELECTRE III	Segment 10	1^{st}	1^{st}	1^{st}	**1^{st}**
	Segment 11	Tie: 2^{nd}	Tie: 2^{nd}	Tie: 2^{nd}	**Tie: 2^{nd}**
	Segment 12	Tie: 2^{nd}	Tie: 2^{nd}	Tie: 2^{nd}	**Tie: 2^{nd}**

The first sensitivity iterations used equal criteria weights and no assignment of fuzzy criteria relationships. This lack of stakeholder preference resulted in no distinct ranking between many pairs of river segments in Groups 1 and 2. This result is important because little distinction is made when comparing the impairment classes of criteria in river segments when stakeholder preferences are not incorporated into a formal decision analysis.

The integration of stakeholder-driven criteria weights and fuzzy criteria relationships resulted in the same overall ranking among river segments in Groups 1 and 2 for both MCDA methods. This result is important because we aimed to control for differences in the assumptions of each MCDA method and conclude that they did not have an overall impact on the results. The prioritization of river segments in Group 3 was very similar, regardless of the inclusion of criteria weights or sensitivity iteration.

To summarize the results in the context of environmental flows management, we view the highest ranked Segments 2, 7 and 10 (Figure. 2.1; Table 2.8) are highly impaired and are considered priority options for the basin roundtable to deliberate future site-specific projects and policies that support flow interventions. Examples of such projects include: i) potential flow modification projects from upstream impoundments, and ii) water rights transfer agreements from consumptive uses (e.g., water supply and agriculture) to non-consumptive uses (e.g., hydropower and recreation). Low ranking Segments 1, 6, 11 and 12 are the least impaired and are considered priority options for environmental flow preservation policies.

Table 2.8 River segment rankings per basin group

Group 1	Segment 1	4^{th}
	Segment 2	1^{st}
	Segment 3	2^{nd}
	Segment 4	3^{rd}
Group 2	Segment 5	2^{nd}
	Segment 6	5^{th}
	Segment 7	1^{st}
	Segment 8	3^{rd}
	Segment 9	4^{th}
Group 3	Segment 10	1^{st}
	Segment 11	Tie: 2^{nd}
	Segment 12	Tie: 2^{nd}

Most sensitivity iterations of PROMETHEE II yielded the same ranked relationships for Groups 1 and 2. This gives strength to the order of river segments as management priorities in the basin. However, two sensitivity iterations of ELECTRE III gave alternative ranking relationships. For example, Segment 10 and Segment 14 equally ranked in two iterations. This inconsistency among the outranking methods is believed to be due to the following: i) the discordance metric in ELECTRE III, and ii) the assumptions of transitivity in PROMETHEE II. Two outranking methods are used in this analysis for the benefit of knowing how each differs with respect to how they prioritize river segments. ELECTRE III tries to find the most favorable river segment overall, avoiding the potential impact that extreme criteria conditions may skew a river segment ranking. Results were checked by conducting multiple iterations that used different veto thresholds and found that discordance reduces the strength of an outranking relationship in ELECTRE III. Likewise, the method ignores the transitivity assumption that exists in PROMETHEE II. Therefore, results from the ELECTRE III method may reflect more completely the uncertainties of Yampa-White Basin stakeholders, whose preferences we elicit may not explicitly represent rationality all the time.

Intermediate ranks from the sensitivity analysis yielded interesting caveats for flow management in Groups 1 and 2. To give an example from Group 2 where both trout and riparian vegetation were highly preferred criteria, we noticed that Segment 8 was equally favoured to Segment 5 when uncertainty was included as a linear fuzzy relationship for all three basin criteria. Likewise, Segment 5 ranked higher in iterations where stakeholder preference was simulated as being strictly indifferent towards riparian vegetation. According to this sensitivity iteration, the AHP weights were integrated with stakeholder feedback to ask whether riparian vegetation should be considered a high management priority (i.e., given less flexibility to its current flow-based impairment status) and, if so, what outcome would it have on the ranking of the five river segments in the group. The ecological merit behind these sensitivity iterations is that managing for riparian vegetation may have an integrated positive effect for instream criteria in this group (i.e., "the valley rules the stream"; Hynes, 1975). It was determined that if stakeholders are more uncertain about trout impairment and are flexible to consider riparian vegetation as a preferred upper basin criteria, then Segment 5 may be considered an important flow management priority in Group 2. This outcome was well-received through *a posteriori* conversations with volunteer basin roundtable members.

We stress here the importance of creating logical sensitivity iterations using *a posteriori* stakeholder feedback including discussions about the preference survey and in-person discussion of results. Because this was a collaborative effort, we tended to steer away from sensitivity analyses that were unimportant to the decision context and project goals. The feedback procedure is suggested as a means of gauging how many sensitivity iterations of the MCDA techniques are needed to develop a defendable rank.

Conclusions

To carry out a systematic social process conducive to the ELOHA framework for regional environmental flow assessment, a collaborative decision analysis and electronic support tool was developed to prioritize basin criteria and to rank river segments in support of stakeholder-defined environmental flow management preferences. The planning project produces a template that can be incorporated into future ELOHA applications in other geographical and governance contexts.

Our multi-faceted decision analysis used multiple methods for MCDA to validate the decision support tool. However, the WFET study did not estimate impairment classes of all criteria at all basin river segments and we cannot provide a whole basin ranking. The decision analysis is limited to comparing river segments with similar criteria and, hence, no distinction can be made among low and high priority river segments across the three basin groups in Table 2.8. Comparisons among the basin groups and other river segments not used in the decision analysis require further investigation.

We consider the approach to design the objectives hierarchy and preference survey as objective methods for correcting and detecting potential stakeholder bias. Only 11 members of a larger stakeholder basin roundtable were requested to participate. Our results are illustrative of the kinds of priorities stakeholders in the basin may associate to the river segments. The intent was for survey participants to ignore place-based knowledge of the river segments and to focus on basin-wide non-consumptive use management. It is questionable as to whether the resulting criteria weights would have changed had there been a different hierarchical structure to the decision problem or different style of questioning. For example: Would the criteria weights have changed if the river segment options were made available to the stakeholders? Addressing this question would necessarily involve an element of geographical preference. Yet the criteria weights ultimately make management sense based on *a posteriori* discussions and an understanding of ecological and socioeconomic characteristics of the Yampa-White River basin.

The decision support tool was developed in Microsoft Excel versus other sophisticated MCDA packages for easy access and distribution among the scientists, analysts and basin roundtable members involved in the project. We are confident that future approaches will develop similar tools that are transparent and interactive and are applicable to environmental flow or ELOHA decision making.

CHAPTER 3: A PROPOSED DECISION FRAMEWORK FOR SYSTEMATIC RIVER RESTORATION PLANNING

Summary

Human-driven alterations to freshwater ecosystems are leading to a global decline of river function and biodiversity. Recently, concepts and methods from decision analysis have been used to grow the field of river restoration, such that biophysical and socioeconomic expertise is incorporated into a systematic planning procedure and tradeoff analysis that is employed before restoration actions are implemented. In this chapter, a decision framework is proposed for systematic river restoration planning. With the framework, key concepts from decision analysis are used to systematically design and formally evaluate Pareto efficient tradeoffs associated with alternative restoration strategies within a watershed, and to provide a short-list of viable restoration alternatives to decision makers for implementation. The proposed framework has the capacity to make technical science-based information and sophisticated decision support methods transparent for stakeholder deliberation and implementing restoration policies. To illustrate the framework, I draw from a published restoration case study in South East Queensland, Australia.

Introduction

The worldwide degradation of river ecosystem function and freshwater biodiversity (Strayer and Dudgeon, 2010) has led to the development of restoration strategies, which generally aim to improve the biophysical structure and function of ecosystems toward socially desirable biophysical conditions. The field of river restoration has been comprehensively reviewed (USNRC, 1992; Palmer et al., 2014) and awarded substantial government (Bernhardt et al., 2005; Brooks and Lake, 2007) and private funding. Yet criticisms of the practice of river restoration are extensive. Scientific concerns include the “scale” of restoration projects, many of which are very local and restricted to river reaches with easy land access (Wohl et al., 2005; Alexander and Allan, 2007; Beechie et al., 2010). Additional concerns are the failure to select functionally important ecological processes that contribute to successful restoration (Lake et al., 2007; Palmer et al., 2010) and a lack of post-restoration monitoring to evaluate success (Palmer et al., 2005; Roni et al., 2008). More general critiques include claims that integrated methods for planning catchment-scale restoration projects are under-utilized (Palmer and Bernhardt, 2006; Hermoso et al., 2012) and that philosophical approaches to restoration fail to combine biophysical and socioeconomic expertise to more deeply inform decision makers on how to evaluate restoration options (Hermoso et al., 2015).

Historically, river restoration decisions were implemented using *ad hoc* approaches where many different sources of information were gathered to develop actionable strategies with independently predicted outcomes (Hermoso et al., 2012). To account for this and many other criticisms, planning for river restoration is becoming increasingly structured and systematic by applying concepts and methods from decision analysis. Broadly, decision analysis is a stepwise stakeholder negotiation process that employs systems of methods to aid decisions to “wicked” resource management problems (Rittel and Webber, 1973), which are characterized by having multiple management objectives, conflicting stakeholder values, conflicting data requirements, and disagreement or incomplete knowledge on methodological assumptions (i.e., deep uncertainties). Keeney (1982) decomposes classical decision analysis into four linear steps, whereas Failing et al. (2013) describe a cyclical process that is applied directly to ecological restoration. In general, decision analysis for planning restoration emphasizes the following components:

1. Problem definition
2. Identifying restoration objectives
3. Design restoration alternatives that address the problem
4. For each alternative, describe the consequences of each restoration objective through predicted response value tradeoffs and by incorporating uncertainty
5. Assessment of the preferences of stakeholders involved in the problem
6. Prioritization of restoration alternatives using appropriate algorithm or heuristic procedures
7. Implementation of management actions, monitoring, and re-evaluation

Two complementary advances in decision analysis are seldom specified in the general process but are noteworthy for the field of river restoration. First, the principle of Pareto efficiency claims that decisions to enact change cannot make one person better off without making others worse off. This classical economics concept was later used by Koopmans (1951) to quantitatively analyze multiobjective choice problems. The latter development was made so that analysts could effectively search through a region of feasible management consequences (i.e., a geometric hyperplane where the multiple objectives functions of a problem are satisfied) to find a set of Pareto efficient or nondominated consequences, such that moving from one alternative set of consequences to another may provide gains in the performance of one management objective while simultaneously imposing losses to other objectives.

An important purpose of Koopmans' translation of the Pareto efficiency principle was to design management alternatives based on the problem dimensions (i.e., continuous space between the upper and lower bounds of the objectives) and not on pre-defined social preferences (Goicoechea et al., 1982). Stakeholders may be involved in developing analytical models for the management objectives, but they don't pre-constrain the problem to a degree that only a limited set of management alternatives are feasible. This is important because stakeholders want to be given many options that are workable within spatial, temporal, operational, or budgetary constraints of the system. Analytical methods for multiobjective optimization are popular because they can seek a Pareto efficient set of alternatives by combining simulation with mathematical optimization calculations that efficiently develops and searches through feasible regions of management consequences. Figure 3.1 gives an example of how the Pareto efficiency principle may be applied to river restoration.

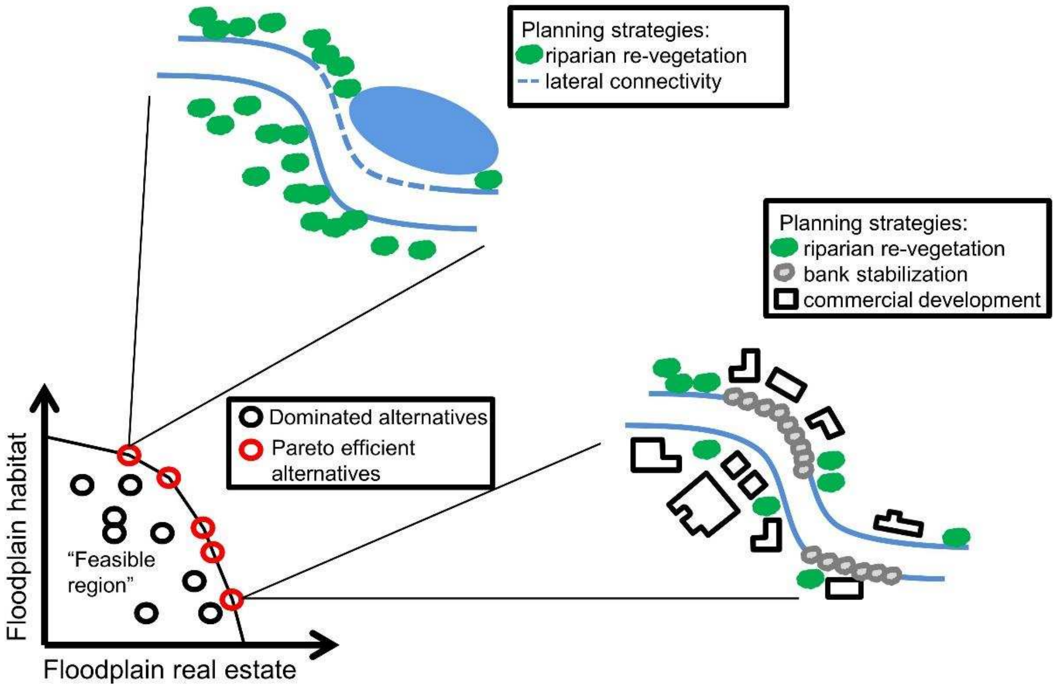

Figure 3.1 Simple example of a Pareto efficiency graph and diagrams of feasible restoration alternatives that tradeoff habitat and real estate objectives in river floodplains. The Pareto efficient alternatives are differentiated from the feasible set because they dominate others but not each other. Seeking a different Pareto efficient restoration alternative will yield a different set of restoration strategies to improve one objective at a cost of decreasing the performance of others.

The second advancement that complements the Pareto efficiency principle is dominance theory, which aims to investigate the relationships among the consequences of discrete management alternatives based on incorporating human judgments into a tradeoff analysis. Different methods for dominance evaluation have been developed to address the prioritization of discrete management alternatives. Valuation approaches like the simple multiattribute rating technique (Otway and Edwards, 1977) aim to maximize the expected utilities of management objectives and are based on agreement with the economic principles of human rationality like transitivity and more-is-better (von Neumann and Morgenstern, 1944). With these methods, algorithms are used to estimate a utility function for each alternative that satisfies stakeholder preferences for the objectives. Thus, a dominance relationship is established where alternatives are either more valuable than others (i.e., utility function scores are different among the set) or are indifferent to others (i.e., scores are the same among alternatives).

In contrast to valuation methods, "satisficing" (Simon, 1956) methods use heuristic procedures to evaluate management alternatives where an optimal decision cannot be guaranteed. Rather, it is believed that a dominance relationship can be established that satisfies the constraints of the problem or are good enough for decision making by incorporating human preferences or aspiration levels for the management objectives into the tradeoff analysis. Analysts use procedures like ELECTRE (Roy, 1996) to enrich our understanding of the dominance relationships among the tradeoffs without transforming each alternative into a utility function. Heuristic search methods are especially useful when the underlying complexities of the problem are poorly understood and when the axioms of rationality are relaxed. Accordingly, fuzzy logic (Zadeh, 1965) is a well-established field for comparing alternatives with conflicting objectives and different performance measures (numeric or symbolic).

This chapter proposes to incorporate the Pareto efficiency and dominance concepts into a decision framework for *systematic river restoration planning*. The proposed framework combines modern planning tools to inform the decision making process that is employed prior to implementing restoration projects. Results of a literature reviewed are described relative to the framework and illustrate its potential value to inform decision making with a case study that draws on published work in South East Queensland (SEQ), Australia (Hermoso et al., 2015). In this chapter, I aim to convey the advantages and disadvantages of applying the Pareto efficiency and dominance concepts to river restoration in order to provide a blueprint for balancing socio-environmental information into planning projects. This allows analysts to deliver technical but transparent planning materials to decision makers regarding the design and evaluation of tradeoffs associated with many possible future restoration actions and policies

Methodological framework

A proposed decision framework for systematic river restoration planning is described as an environmental systems analysis process occurring in a social-scientific context with elements of hierarchical planning phases along with feedback loops (Figure 3.2). In the agenda setting phase, stakeholders and decision analysts convene to agree on restoration planning goals and to identify important and measurable (i.e., outcome-oriented) socio-environmental performance objectives that are linked to the study area. The concept of modeling and managing anticipated impacts within social-ecological systems for long-term planning is a research frontier (Liu et al., 2007) that is not well-established for river restoration. Identification of possible land use types and parcel locations where restoration actions may be implemented are identified to provide boundaries for the planning context. It is presumed that planning at larger catchment scales allows connectivity of restoration responses throughout the river network and the maximum possible number and type of land use parcels are considered for restoration actions (see case study illustration below).

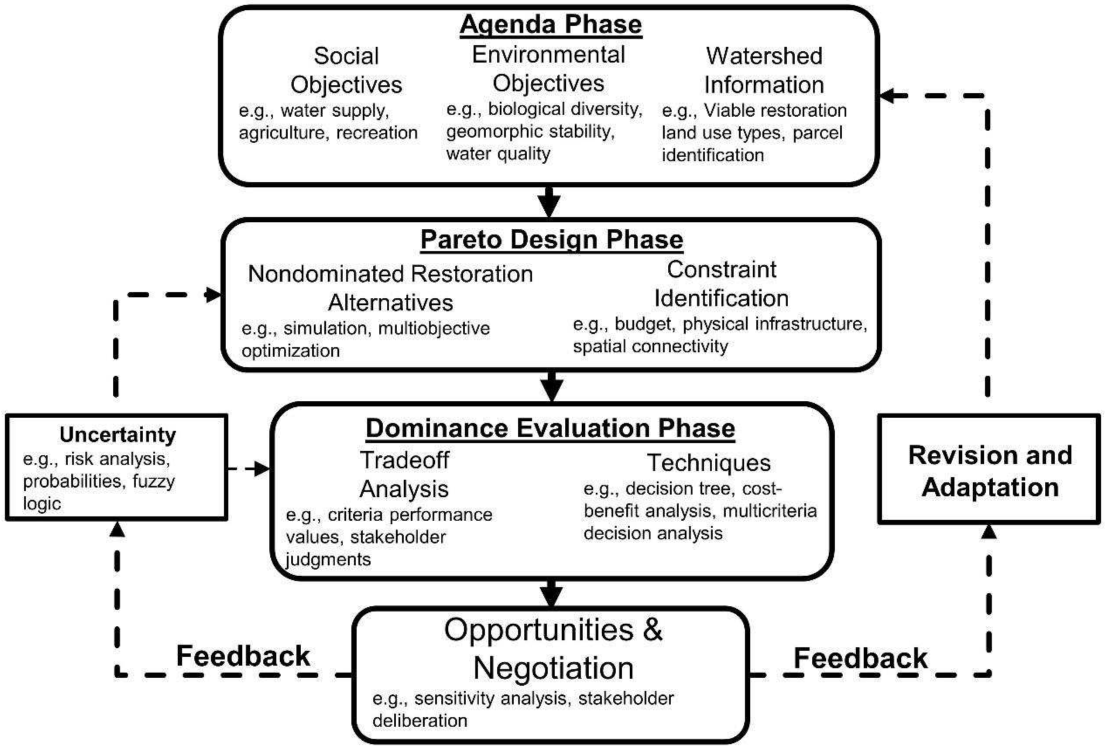

Figure 3.2 Proposed conceptual decision support framework for systematic river restoration planning

The Pareto design phase is performed to systematically establish Pareto efficient restoration alternatives. Predictive modeling platforms (Reichert et al., 2007) for the management objectives are used to quantify potential hydro-ecological or other metric-related restoration responses based on implementing a restoration action on a land use parcel in a catchment.

Traditionally, the development of Pareto efficient alternatives were performed *ad hoc* by manually varying the problem parameters between upper and lower feasible objective values (e.g., David and Duckstein, 1976). However, quantitative derivation of Pareto efficient alternatives has become easier with computers and modern programming software. The broad family of metaheuristic optimization algorithms (e.g., genetic algorithms, neural networks, simulated annealing) among other combinatorial simulation and optimization methods (Simon, 2013) allow for many different linear or non-linear predictive models to be integrated as decision levers in iterative searches over numerous feasible objective performance combinations that each satisfies the problem constraints. By incorporating these tools for multiobjective optimization, the methods converge on a set of Pareto efficient alternatives (for reviews in the context of water management, see Labadie, 2004; Jager and Smith, 2008). Results are typically communicated in graphs that show the tradeoffs in socio-environmental condition linked to each Pareto efficient alternative that is kept from performing the iterative search procedure (Figure 3.1) (for other graphical examples, see Null and Lund, 2011; Steinschneider et al., 2013; Herman et al., 2014; Rheinheimer et al., 2015).

The aim of the dominance evaluation phase is to perform analytical procedures on the measured outcomes from the Pareto design phase that filters the set of restoration options to a smaller set of the most dominant options for stakeholder deliberation. Identifying a sub-set of priority restoration alternatives is easier for deliberation, especially if there is a large multidimensional set of objectives and alternatives. Performing this tradeoff analysis solely with the measured outcomes (i.e., restoration response values for each alternative) reduces the degree of preference (e.g., geographical) that may be assigned by stakeholders. Many river restoration studies have used these techniques for prioritizing sets of restoration options (see Table 3.1; for a review of methods and water management applications, see Hajkowicz and Collins, 2007) including the illustration presented in this chapter.

Understanding the opportunities for decision-making and negotiating restoration implementation is a final step of the framework. This is loosely defined as an exercise of disseminating relevant results of the Pareto design and dominance evaluation phases directly to stakeholders. New knowledge (i.e., sensitivity analysis, uncertainties, feedback on model parameter changes) is incorporated via direct decision maker interaction so that the planning assessment can be improved in an adaptive learning cycle prior to on-the-ground restoration actions being implemented. For example, sensitivity analyses may incorporate alternative measures of risk for predictive model performance (e.g., climate change, financial) (Herman et al., 2014). Many current river restoration case studies suffer from insufficient monitoring and lack of foresight for changing environmental indicators and adaptation planning (Palmer et al., 2005, Bernhardt and Palmer, 2011). The proposed framework aims to address foreseeable complications in the planning process by incorporating sensitivity information and addressing social preferences prior to implementing restoration strategies.

Literature review

To identify strengths and weaknesses within the current body of river restoration planning applications, the primary literature was surveyed relative to the described framework. I screened many possible applications and chose to include published studies that specifically evaluated multiple restoration alternatives in a decision making context that aimed to examine competing ecological and social management objectives and tradeoffs. This significantly reduced the amount of case studies to analyze. Additionally, articles were selected that spanned a range of decision contexts (e.g., different management objectives, spatial scale, etc.).

Results from the literature review (Table 3.1) indicates that incorporating systematic Pareto design phases (i.e., no *ad hoc* design of restoration alternatives) into formal dominance evaluation phases are rarely used for the advancement of systematic river restoration planning. I presume this to be a result of lacking cross-disciplinary experience, especially expertise on formal tradeoff analysis incorporating value judgements and uncertainties.

Table 3.1 A survey of river restoration planning frameworks and applications related to the proposed decision framework.

Problem definition	Agenda phase	Pareto design	Dominance evaluation	Sensitivity analysis	Comments	Citation
Four riparian re-vegetation options are developed and prioritized from several stakeholder groups of north Queensland, Australia	X	X	X	X	- Pareto efficient restoration alternatives were designed *ad hoc* - Sensitivity analysis was based on incorporating three decision analysis methods into a dominance evaluation based on independent preferences from each stakeholder group and comparing the results	Qureshi and Harrison (2001)
Prioritization of basins and sub-basins based on qualitative and quantitative features within Zuni Reservation, New Mexico (USA)		X	X	X	- Restoration alternatives appeared to be Pareto efficient (though maximizing agent for watershed objectives was not specified) - Sensitivity analysis was based on incorporating stakeholder-assigned weights into a general weighted average decision analysis (see Eq 1.1)	Gellis et al. (2001)
Five alternative water allocation options to restore fish and wildlife habitat in the Missouri River system (USA) were prioritized using valuation methods		X	X	X	- Pareto efficient restoration alternatives were designed *ad hoc* - Sensitivity analysis was based on incorporating hypothetical stakeholder weights into the decision analysis	Prato (2003)
Five river restoration options on a reach of the Thur River (Switzerland) were evaluated with value-based stakeholder decision analysis		X	X	X	- Pareto efficient restoration alternatives were designed *ad hoc* - Sensitivity analysis included performing structured stakeholder preference surveys	Hostmann et al. (2005)

Stakeholder negotiation process to improve water management along a river reach in the White River Watershed, Vermont (USA)	X	X	X		- Pareto efficient restoration alternatives were designed *ad hoc* - Dominance evaluation included ranking the restoration alternatives based on individual and group stakeholder preferences for the management objectives	Hermans et al. (2007)
Development of tradeoffs associated with fish recruitment economic cost applied to water allocations in the Shasta River system, California (USA)		X			- Pareto efficient restoration alternatives were designed with multiobjective optimization software - No formal dominance evaluation, only description of tradeoffs	Null and Lund (2011)
Case study approach in Victoria, Australia, for applying multiobjective optimization to develop water allocation schedules for benefitting irrigation and instream ecological function		X			- Pareto efficient restoration alternatives were designed with multiobjective optimization software - No formal dominance evaluation, only description of tradeoffs	Powell et al. (2013)
Experimental decision making process for flow-based habitat restoration on Lower Bridge River,	X	X			- Superior description of stakeholder negotiation process - Restoration alternatives appeared to be Pareto efficient (though objective performance values were not listed for each alternative) - Pareto efficient restoration alternatives were designed *ad hoc* - Deliberative stakeholder evaluation of restoration alternatives was performed	Failing et al. (2013)
Case study approach in South East Queensland, Australia, for apply	X	X			- Pareto efficient restoration alternatives were designed with multiobjective optimization software - No formal dominance	Hermoso et al. (2015)

multiobjective optimization to develop socio-environmental restoration planning strategies whole catchments.					evaluation, only description of tradeoffs	

Illustration of the framework

Based on the results of the literature review, an illustration of the proposed decision framework was desired. To show the value of moving a restoration planning problem through the steps of the proposed framework, agenda setting and Pareto design methods and results from a recently published article (Hermoso et al., 2015) were complemented with dominance evaluation and sensitivity analysis phases to provide insights on how information regarding socio-environmental tradeoffs associated with many possible restoration alternatives may be used for stakeholder deliberation and project implementation.

Study area and planning context

The Hermoso et al. (2015) case study was performed in the upper Bremer River catchment, which is a tributary of the Brisbane River in SEQ, Australia (Figure 3.3). Restoration is especially needed in this area given that SEQ is experiencing rapid population growth and subsequent modifications and impacts to freshwater ecosystems. Approximately two thirds of the native vegetation has been cleared since European settlement, and grazing currently occupies more than 35% of the region. Non-urban sediment loads, mainly from gully and channel bank erosion, have been identified as a cause of poor water quality and aquatic ecosystem health in freshwater and estuarine/marine systems of the region (Olley et al., 2014).

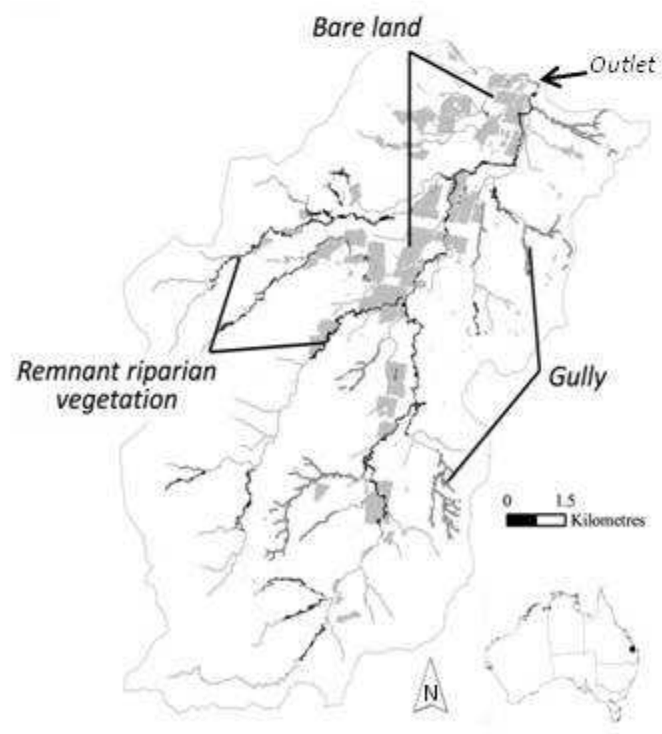

Figure 3.3 Map of the upper Bremer River catchment. Many parcels of three land use types (bare land, gullies, remnant riparian) were identified for possible restoration planning strategies (*Source*: Hermoso et al., 2015).

Pareto design of restoration alternatives

In the agenda phase of the planning project, three main objectives were determined for the catchment from a collaborative needs assessment with South East Queensland Water, a local water authority that manages water supply in the region and is tasked with planning for future water needs. The objectives pursued by the project are important for long-term socio-environmental health and include: i) maximizing the reduction of sediment loads throughout the catchment, ii) maximizing ecological health of important catchment waterways, and iii) minimizing the socioeconomic impact (i.e., commercial development) from locating restoration actions on viable land use parcels (Figure 3.3) throughout the catchment. Details on how management objectives were developed and modeled in the catchment is provided in Hermoso et al. (2015).

An iterative metaheuristic selection method called multiobjective simulated annealing (MOSA) was used to iterate multiple combinations of restoration actions and catchment parcels. Each feasible restoration alternative tested during the MOSA procedure computed a unique combination of restoration actions and their spatial allocation on land use parcels throughout the catchment, measured the predicted restoration response of an objective at the parcel, and routed the cumulative (i.e. additive) responses from each parcel throughout the linked catchment network to the outlet where a single downstream response for each of the three catchment objectives was estimated. The process converged on a configuration of Pareto efficient restoration alternatives as the cumulative restoration response values or tradeoffs of objectives associated with one alternative are compared to alternatives developed at previous iterations to check that they are not better or worse than others. For demonstration purposes, all potential restoration alternatives were constrained to a maximum budget of AUD $1 Million to maintain a realistic budget.

The iterative MOSA process resulted in coding tens of thousands of feasible permutations and converged to a set of 566 Pareto efficient restoration alternatives (Hermoso et al., 2015). Each Pareto efficient alternative that was kept recorded a different spatially-distributed set of restoration actions at relevant land use parcels throughout the catchment. The spatial location of restoration actions for each alternative was logged for future stakeholder deliberation (i.e., spatial analysis). The cumulative response of the catchment traded off sediment load values with ecological health values (Figure 3.4). Restoration actions to improve ecological health throughout the catchment resulted in a higher socioeconomic impact on the productivity of un-restored land use.

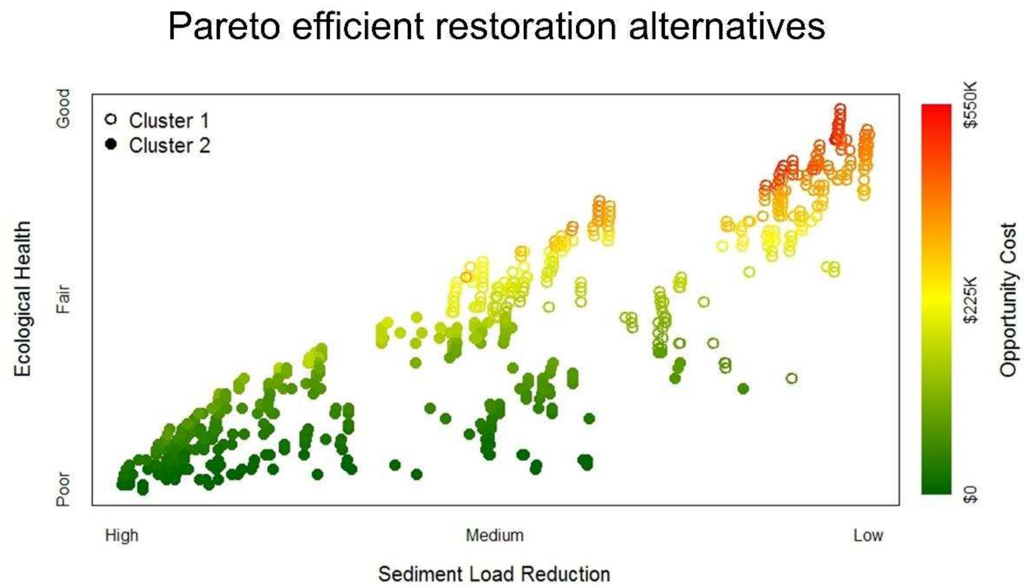

Figure 3.4 Pareto efficient restoration alternatives for the upper Bremer River catchment as optimized by Hermoso et al. (2015). Each point corresponds to a unique set of spatially-distributed restoration actions throughout the catchment. Two clusters (empty and filled dots) were developed to establish sets of contradictory restoration alternatives that tradeoff similar objective values for dominance evaluation.

The conflicting tradeoff between sediment load and ecological health was a result of pre-determining suitable restoration strategies for those objectives in the catchment. To reduce sediment loads throughout the catchment, many types of gully interventions were recommended (Olley et al., 2010), which became expensive and used most of the AUD $1 Million budget. Restoration actions to improve the ecological health metric (e.g., riparian restoration and bare land re-vegetation) did not improve sediment quality as effectively as gully restoration throughout the catchment. Additionally, those actions tended to use up more possible land use parcels for commercial development than actions that improve sediment loads and therefore resulted in a higher opportunity cost to the catchment. It is unclear whether long-term data and MOSA iterations may change these inverse relationships, but theoretical aquatic science informs that sediment loads may have a more positive relationships with instream ecological health indices over the long-term (Wohl et al., 2015).

Dominance evaluation

A method for fuzzy compromise programming (FCP) (Bender and Simonovic, 2000) was used in conjunction with an objective cluster analysis to describe the dominance relationships of the tradeoffs from the MOSA results for stakeholder deliberation. The compromise programming method (Zeleny, 1973) was originally developed to rank Pareto efficient results to a multiobjective optimization algorithm based on visualizing the alternatives as a multidimensional dataset and finding alternatives with cumulative objective performance values as close as possible to an "ideal" but non-feasible one. An ideal alternative is generally considered to possess the highest achievable cumulative response values from each management objective in the set of Pareto efficient alternatives. Compromise programming has been successfully used in case studies to evaluate the dominance of river management options with emphasis on impacts to water resources and reservoir operations (Duckstein and Opricovic, 1980; Shiau and Wu, 2006).

The FCP algorithm uses the family of distance metrics L^p to evaluate the multidimensional dataset of alternatives a_i with objective performance values z_j. The following problem formulation for compromise programming was used to rank the plans:

$$minimize\ L^p(i) = \sum_{j=1}^{m} w_j^p \left|\frac{z_j^* - z_j(a_i)}{z_j^* - z_j^{**}}\right|^p \tag{3.1}$$

for alternatives $i = 1, \dots, n$; objectives $j = 1, \dots, m$

where p is a distance norm; w_j is the relative importance factor of the objective; z_j is the objective value of i^{th} alternative; z_j^* is the ideal objective value over all Pareto efficient restoration alternatives; and z_j^{**} is the worst objective value over the plans. The Euclidean or least squares distance norm ($p = 2$) was used to perform the ranking because I wanted the deviations from “ideal” to be weighted in proportion to their magnitudes.

The raw multidimensional dataset of objective performance values was re-scaled into two fuzzy sets of numbers for dominance evaluation for two reasons. First, the ecological health values were less differentiated than the other objectives in the MOSA results (Hermoso et al., 2015). Second, it was desirable to incorporate uncertainties in the level of social preferences for the cumulative response values as they related to satisfactory watershed management. The first fuzzy set was developed using normalized distance measures to linearly scale the raw objective values into a fuzzy membership function $P(D)$ between 0-1 (Figure 3.5a). The re-scaled data represented the proportion of the highest or ideal objective values and maintains differentiation. Indeed, I presumed that decision makers want to find alternatives as close as possible to the highest achievable values from the MOSA permutations.

The second z-shaped fuzzy set was calculated based on simulating hypothetical stakeholder aspiration levels for the cumulative objective performances in the catchment (Figure 3.5b). With this fuzzy set, I presumed that decision makers do not expect to attain the highest achievable objective values with the restoration strategies and would rather agree on aspiration or satisficing levels for the objectives based on investigating the MOSA results. For example, catchment sediment loads for the Pareto efficient alternatives varied between 5,322 tons/yr (lowest) to 2,729 tons/yr (ideal) (Hermoso et al., 2015). Two indifference thresholds were specified for sediment where a cumulative load of 3,000 tons/yr or less were determined to be the aspiration level (a), loads above 4,500 tons/yr were determined undesirable (b), and loads in-between were normalized based on their distances from these values. Similar determinations were made to maximize ecological health $(a = 49.26\ units, b = 48.765\ units)$ and to minimize opportunity costs $(a = AUD\ \$100{,}000, b = AUD\ \$500{,}000)$.

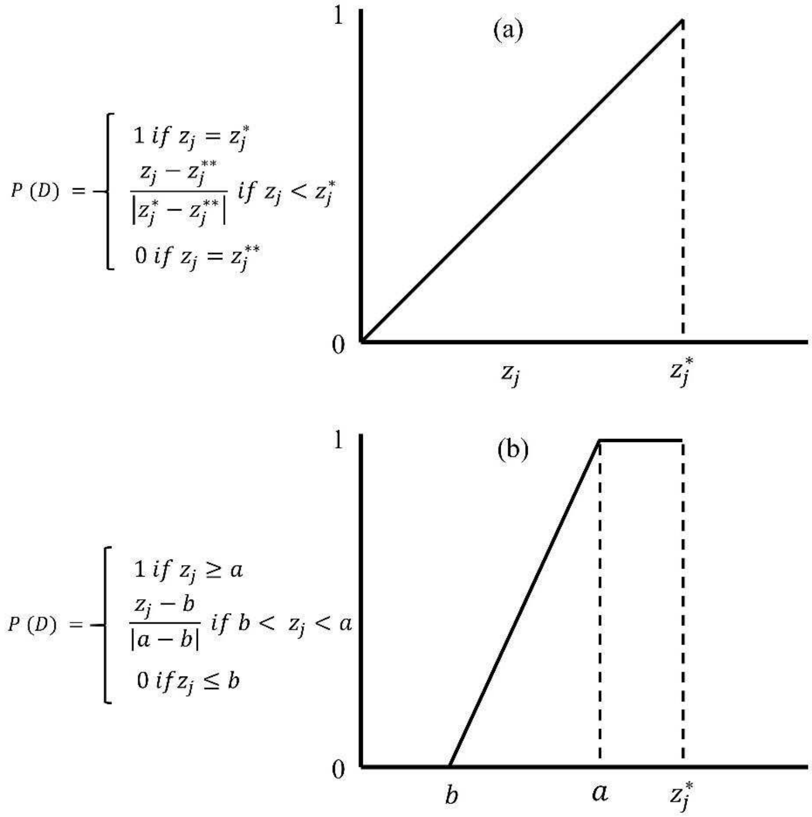

Figure 3.5 Fuzzy distance metrics used to perform the dominance evaluation phase in the case study illustration. (a) A linear fuzzy set of membership function values was calculated by re-scaling the raw objective performance values based on normalized distance measures. (b) A z-shaped fuzzy set was calculated based on simulating stakeholder-defined objective values, which incorporated more uncertainty in the restoration alternatives.

Sensitivity analysis

A unique advantage of using methods for decision analysis to inform decisions is to incorporate a social preference structure into the problem evaluation. Preference judgments of decision makers may be incorporated as importance factors or "weights" (Eq. 3.1) for the problem objectives in the compromise programming method. Although many restoration case studies have developed sensitivity analyses based on including stakeholder-assigned weights (see Table 3.1), stakeholders can be unreliable or unwilling to entrust such information to analysts, especially if preferences change over time. Stakeholder feedback for performing a dominance evaluation was not included in this framework illustration. Rather, I objectively simulated social preferences with development of two decision viewpoints: i) a preference-neutral evaluation based on performing FCP on the complete fuzzy set of all 566 nondominated alternatives, and ii) a cluster analysis based on clustering the fuzzy sets and performing FCP iterations on each.

First, a preference-neutral ranking of the complete fuzzy sets was performed using equal objective weights, which yielded a preference-neutral compromise among all Pareto efficient restoration alternatives. The ranking on the z-shaped fuzzy set incorporated more uncertainty in the objective values than by using the linear fuzzy set. The ideal values and worst objective values for these FCP iterations were $z^* = 1$ and $z^{**} = 0$.

Next, the two fuzzy sets of membership functions were clustered by using the K-means clustering algorithm (MacQueen, 1967), which is among the most popular and simplest data clustering methods (Jain, 2010). The K-means package from the R programming environment (Maechler et al., 2014) was used to organize the scaled data into two clusters based on minimizing the squared difference (i.e., Euclidean distance) between the empirical mean of each cluster and the alternatives inside the cluster. Since the dataset depicted two distinct regions of objective tradeoffs (Hermoso et al., 2015; Figure 3.4), two clusters were specified with the aim of providing mutually contradictory sets of priority restoration options for stakeholder deliberation. It was believed that identifying more clusters would weaken this assumption and would likely muddle stakeholder deliberations.

After performing the cluster analysis, Linear Cluster 1 included 278 restoration alternatives and z-shaped Cluster 1 included 291 alternatives with better ecological health values but poor sediment load values throughout the catchment, and they incurred the highest opportunity costs for commercial land development on the parcels chosen for each alternative. By contrast, Linear Cluster 2 included 288 alternatives and z-shaped Cluster 2 included 275 alternatives that represented the lowest catchment sediment loads and low opportunity costs but poor ecological health values. FCP iterations were performed on the four clusters of re-scaled alternatives with characteristically similar objective tradeoffs in the alternatives. Sensitivity iterations performed on the clusters had different z_j^* and z_j^{**} values that pertained to the different scaled objective values in each cluster.

Opportunities for decision makers

The highest ranked plans for each FCP iteration are considered priorities for decision maker deliberation (Tables 3.2 and 3.3). Important information can be gleaned from investigating the tradeoffs among the highest ranked plans, which is useful information to deliver to stakeholders for negotiation. Therefore, the following limited discussion is meant to communicate the distinctions made between the tradeoffs in the highest ranked restoration plans using Tables 3.2 and 3.3.

Table 3.2. Top 10 ranked restoration alternatives based on linearly scaled objective values are displayed from each sensitivity FCP iteration.

	Linear (preference-neutral compromise)				Linear Cluster 1 (better options for ecological health improvement)				Linear Cluster 2 (better options for sediment load reduction)			
Rank	Alternative	Sediment load	Ecological health	Opportunity cost	Alternative	Sediment load	Ecological health	Opportunity cost	Alternative	Sediment load	Ecological health	Opportunity cost
1	185	0.73	0.37	0.70	460	0.42	0.61	0.55	216	0.80	0.25	0.86
2	186	0.73	0.36	0.73	459	0.42	0.60	0.57	217	0.80	0.24	0.87
3	226	0.78	0.32	0.77	419	0.52	0.60	0.50	296	0.74	0.31	0.82
4	187	0.73	0.35	0.74	442	0.46	0.63	0.47	295	0.74	0.28	0.84
5	221	0.74	0.33	0.75	342	0.41	0.63	0.51	218	0.77	0.27	0.84
6	298	0.74	0.32	0.79	461	0.42	0.59	0.57	294	0.74	0.25	0.86
7	296	0.74	0.31	0.82	421	0.52	0.59	0.51	231	0.80	0.23	0.87
8	227	0.78	0.31	0.77	332	0.43	0.60	0.53	203	0.86	0.25	0.82
9	308	0.79	0.29	0.79	458	0.43	0.57	0.59	297	0.73	0.27	0.84
10	429	0.65	0.43	0.62	435	0.48	0.57	0.54	202	0.86	0.24	0.83

Scaled values are a proportion of the highest achievable and, therefore, values closer to unity (1) offer better restoration benefits for the objectives.

Table 3.3. Top 10 ranked restoration alternatives based on z-shape scaled objective values are displayed from each sensitivity FCP iteration.

	z-shaped (preference-neutral compromise)				z-Shaped Cluster 1 (better options for ecological health improvement)				z-shaped Cluster 2 (better options for sediment load reduction)			
Rank	Alternative	Sediment load	Ecological health	Opportunity cost	Alternative	Sediment load	Ecological health	Opportunity cost	Alternative	Sediment load	Ecological health	Opportunity cost
1	185	0.72	0.41	0.84	419	0.35	0.76	0.57	226	0.80	0.33	0.93
2	186	0.72	0.40	0.87	421	0.35	0.74	0.57	298	0.72	0.33	0.96
3	187	0.72	0.37	0.89	420	0.35	0.72	0.57	308	0.82	0.29	0.97
4	226	0.80	0.33	0.93	422	0.35	0.70	0.59	296	0.72	0.31	1
5	178	0.73	0.39	0.76	486	0.38	0.73	0.50	227	0.80	0.31	0.93
6	221	0.73	0.35	0.90	423	0.35	0.68	0.60	291	0.73	0.31	0.96
7	429	0.58	0.49	0.73	487	0.37	0.70	0.54	214	0.84	0.27	0.97
8	190	0.74	0.35	0.85	424	0.34	0.66	0.63	307	0.82	0.27	0.99
9	194	0.73	0.37	0.79	457	0.40	0.68	0.55	221	0.73	0.35	0.90
10	227	0.80	0.31	0.93	488	0.37	0.68	0.56	290	0.73	0.29	0.98

Values closer to unity (1) offer better restoration benefits for the objectives.

Upon inspection of the results of the Linear dominance evaluation (Table 3.2), I determined that the top two ranked restoration alternatives 185 and 186 are equally important priorities to catchment restoration planning for several reasons. First, both alternatives reduce sediment loads throughout the catchment equally. Although alternative 186 provides a lower opportunity cost than alternative 185, the difference in ecological health scores between the top two plans is the cause of the compromise programming algorithm ranking plan 185 slightly higher than alternative 186. Since the tradeoffs are so close, both solutions are equally important priorities for catchment restoration that decision makers should deliberate among. This trend does not follow to the third ranked alternative 226 because the tradeoff in objective values become more distinct. I determined that considering the tradeoffs further would place a preference for sediment load and would be a disservice to this preference-neutral sensitivity evaluation.

When uncertainty was added to the preference-neutral assessment based on simulating fuzzy stakeholder aspiration levels with a z-shaped membership function (Table 3.3), restoration alternatives 185 and 186 are the highest ranking ones on the full set of restoration alternatives. In contrast to the sensitivity results on the linearly scaled dataset, I recommend incorporating alternative 187 into stakeholder deliberations because the tradeoffs in scaled membership function values for the three alternatives are not distinct enough to determine that alternatives 185 and 186 are better than alternative 187. Based on this dominance evaluation, I determined that restoration alternatives 185, 186, and 187 serve as the better compromise alternatives for balanced socio-environmental decision making in the catchment.

Regarding viewpoints toward improved ecological health (Cluster 1) and sediment load reduction (Cluster 2), distinctions in objective tradeoffs are apparent after the first two or three priority alternatives in the ranking. For example, restoration alternative 217 is the second ranked alternative in Linear Cluster 2 from the viewpoint that trades off ecological health for sediment load and opportunity cost. I considered this alternative to be a priority alongside the highest ranked alternative 216 because it reduced opportunity cost in proportion to the loss in ecological health in the catchment. The next ranked alternatives yielded significantly lower sediment loads and opportunity costs while benefiting ecological health values in the catchment. Since Cluster 2 was considered to be directed toward reduced sediment load and opportunity cost, the lower ranked alternatives are likely undesirable candidates for decision maker deliberation in this context. In sum, I determined that restoration alternative 419 is the better compromise for implementing actions that may significantly improve ecological health because it is ranked highly with both fuzzy sets. Likewise, restoration alternative 296 is the better compromise for implementing actions that may significantly reduce sediment loads and opportunity costs in the catchment.

This dominance evaluation is a key step in decision making processes, especially ones that aim to filter large multidimensional datasets of restoration alternatives. By filtering the number of possible restoration alternatives to a set of better alternatives, advantageous information is provided for project-specific deliberation and spatial analysis by decision makers. Additionally, the dominance evaluation was performed without stakeholder guidance, which makes this evaluation more objective than ones that include preference weighting of problem objectives.

Concluding remarks

In this chapter, I developed a foundation for systematically designing and objectively evaluating Pareto efficient river restoration alternatives within a river catchment. Following a goal of incorporating empirical freshwater science and models into multidisciplinary decision support methods, the proposed decision framework (Figure 3.2) and illustration described in this chapter can be used as a template for cutting-edge systematic river restoration planning around the world.

The illustration is an example of how the described framework may be used and it worked well because a case study for the design phase was previously performed by Hermoso et al. (2015) with sufficient data and predictive models for management objectives. Data availability is important to initiate the systematic planning process. If data availability is a limitation, appropriate measures for uncertainty should be incorporated so that all relevant objectives are included (Failing et al., 2013). Predictive models that use process-based inputs and parameter estimates will guide science-based restoration performance estimates of catchment objectives and consequently injects defensible ecological restoration understanding into the decision making process. Stakeholder preferences on the model parameter estimates were incorporated in the case study described (Hermoso et al., 2015). Changing environmental (climate change) or socioeconomic (financial) indicators were not simulated in the predictive models because catchment-specific information was not available. Yet sensitive forecast information can be incorporated by changing the model structure to accommodate changing environmental and social conditions. Herman et al. (2014) provide a template for including such information into multiobjective optimization, which will likely constrain the heuristic search procedure to choose different land use parcels for restoration actions than would have been chosen without the forecast information.

All 566 Pareto efficient restoration alternatives and the spatial locations of restoration actions for each alternative were delivered to South East Queensland Water, the stakeholders who contracted the work performed in Hermoso et al. (2015). Yet with development of the proposed decision framework I aimed to objectively reduce this number with sensitivity dominance evaluations, which effectively and transparently organized and filtered the tradeoffs so that stakeholders can make more balanced restoration decisions at the catchment scale. Although a limited opportunities and negotiation phase was performed without direct stakeholder interaction, the dominance evaluation methods and sensitivity results are useful for carrying out similar processes on other river restoration planning problems in a systematic and transparent manner.

The effectiveness of implementing restoration alternatives that were designed in this illustration is beyond the scope of this research because I aimed to provide a short list of preferred restoration alternatives to balance socio-environmental response as deliberation points prior to implementing restoration actions. Seeking additional resources like local or state environmental planning departments, federal agencies, or even private restoration consulting firms will aid in reviewing the advantages or disadvantages for applying catchment restoration actions at the identified land use parcels from the short list of preferred alternatives. Likewise, systematic procedures to review the details of preferred restoration alternatives for compliance risks (Thorne et al., 2015) may be of interest to state or federal agencies to guide on-the-ground restoration decisions and adaptive management.

CHAPTER 4: AN OBJECTIVE METHOD TO PRIORITIZE RIVER MANAGEMENT ALTERNATIVES USING MULTI-CRITERIA DECISION ANALYSIS

Summary

Rivers are used to provide many social and environmental services that benefit humanity. Socio-environmental tradeoff analysis is key to balancing disparate and often conflicting interests for sustainable water management, and methods for multi-criteria decision analysis (MCDA) provide a systematic platform for that integration. This chapter describes a new method for MCDA to objectively prioritize water allocation schedules from large multidimensional sets of criteria and alternatives. The method was developed based on a planning study in Victoria, Australia. A combined simulation and multi-objective optimization procedure was previously integrated into a hydrologic catchment modeling network. That process resulted in a large set of viable daily water allocation schedules that traded off long-term irrigation and hydro-ecological criteria performance at the catchment outlet. In this chapter, stakeholders are guided to identify priority water allocations with development of a MCDA method that includes combined multidimensional ordination and cluster analysis to spread the water allocation alternatives onto a two-dimensional plane that contrasts criteria tradeoffs. A geometric distance-based method was performed on the full set of alternatives and on the two identified clusters in multidimensional coordinate space to prioritize the water allocation alternatives in accordance with minimizing the distance of the alternatives to an ideal but non-feasible alternative with the highest achievable criteria performance values. This method complements the use of subjective elicitation procedures to describe the importance of water management criteria for inclusion in a MCDA.

Introduction

Across the globe, rivers are put into the service of meeting human needs and wants (Postel and Richter, 2003). Society depends on rivers to provide important services like water supply and good water quality for domestic consumption, agriculture, industry, transportation, recreation, and aesthetic enjoyment (Brauman et al., 2007). Likewise, river ecosystems transport water, sediment, and nutrients, and they function to maintain adequate habitat and bio-chemical water quality to sustain instream and riparian biodiversity. A fundamental dependence on rivers and the benefits they provide has advanced social interests at the unanticipated cost of environmentally degrading river ecosystems (Gleick, 2003), which threatens global freshwater biodiversity (Richter et al., 1998; Bunn and Arthington, 2002; Strayer and Dudgeon, 2010) and river ecosystem function (Baron et al., 2002; Allan, 2004).

Sustainable water management is a long-term vision to balance the social and ecological freshwater needs of a dynamically changing environment. Applying this vision to real-world water allocation and management problems exposes conflicting tradeoffs between the structural and functional (i.e., ecological) needs of the river ecosystem on the one hand, and the engineering design and operational needs of water infrastructure and associated uncertainties on the other. A shared vision among stakeholders requires collaboration, which may be assisted by structured decision support techniques to prioritize complex water management tradeoffs. To support the decision making process, freshwater scientists are tasked with estimating the ecological needs of rivers (Poff et al., 2003). These are then integrated with societal needs in problem-specific contexts. Clarke (2002) calls the procedure an analytical audit, which includes specifying important and measurable (i.e., outcome-oriented) water management criteria to understand the performance of individual river ecosystems that vary over time and space. Next, ecological or socioeconomic models are used to predict how criteria perform in alternative planning scenarios. Optimization techniques are often applied to prioritize scenarios that benefit societal criteria performance like economic returns while minimizing impairment to environmental criteria.

One of the many components of the field of decision analysis is to approach real-world problems in structured and integrated case studies. This form of structured decision making requires engagement in collaborative planning efforts with researchers and opinion leaders to specify a problem, identify objectives and criteria, develop possible management decisions that tradeoff socio-environmental performance, and to formally prioritize the tradeoffs using quantitative aggregation methods and stakeholder preferences. A sub-discipline of methods for multi-criteria decision analysis (MCDA) is specialized for integrating socio-environmental interests and prioritizing management decisions in a systematic social science process.

The MCDA problem formulation typically includes two components (Belton and Stewart, 2002): i) a set of subjective preference parameters for management criteria, and ii) an algorithm or heuristic search method for tradeoff analysis. The preference parameters are used as non-dimensional scaling factors or weights that describe the relative importance of different criteria being evaluated for each management alternative. Methods for tradeoff analysis aggregate and compare the decision alternatives based on the quantitative criteria performance values and by incorporating measures of uncertainty that simulate risks or imprecisions with the measurements.

MCDA analysis has long endeavored to provide suitable information from which to make well-informed management decisions. Two schools of thought prevail in MCDA analysis. First, preference-neutral evaluations use simplified aggregation techniques and equal (or no) criteria weights to prioritize management alternatives (for a water management example, see Beilfuss and Brown 2010). These MCDA evaluations reveal a set of priority alternatives that present balanced compromises among the problem objectives and criteria. However, because decision makers are inherently inclined to prefer some management criteria over others, these evaluations can yield unrealistic priority options if that selection does not incorporate knowledge of the relative importance of the criteria. By contrast, many MCDA evaluations incorporate criteria weights through stakeholder cooperation.

Using numerical weights to assign the relative importance of management criteria has been regarded as a primary argument against using methods for MCDA (Gershon, 1982). Several water management MCDA case studies have developed preference weighting structures for water management criteria. Prato (2003) ranked water allocation alternatives using a value function aggregation model and four hypothetical criteria weighting scenarios related to ecological, recreational, and agricultural criteria. Srdjevic et al. (2004) used an analytical method that extracted information from actual criteria performance tradeoffs to develop a normalized vector of criteria weights. Other examples have used structured survey methods that directly elicit preference judgments from decision makers (Bana e Costa et al., 2004; Marttunen and Hämäläinen, 2008; Joubert et al., 2003; Papaioannou et al., 2015; Martin et al., 2015) with aims to incorporate decision maker knowledge and realistic stakeholder values into the MCDA evaluation.

In general, MCDA evaluations with preference weighting should only be performed when there is direct interaction with decision makers who can guide the estimation of criteria weights. However, difficulties in eliciting preferences persist (Mareschal, 1988; Lahdelma and Salminen, 2001): i) elicitation methods are time consuming, ii) preference questions and methods to index criteria weights are inconsistent, iii) decision makers are sometimes unreliable and/or have trouble providing straightforward answers and their answers may change over time, and iv) decision makers can be disinterested in providing explicit preference information.

In this chapter, a new objective MCDA method is described to prioritize large multidimensional water allocation alternatives. I aim to move beyond simple preference-neutral MCDA evaluations by providing a manner to objectively associate preference information into a water management decision problem without stakeholder interaction. A method is developed that combines ordination with cluster analysis to systematically evaluate large numbers management alternatives. Tradeoff analysis of large numbers of alternatives are difficult to consider without organization and/or filtering the alternatives using value judgements. Rather, I applied a more objective method using a real-world water allocation planning study in Victoria, Australia. Ordination and graphical tradeoff analysis of multidimensional datasets have been previously used in MCDA (Clarke and Rivett, 1976; Rivett, 1977; Stewart, 1981; Mareschal and Brans, 1988; Stewart, 1992); however, they are uncommon for water management case studies, especially in conjunction with cluster analysis.

Methods

A combined ordination and cluster analysis MCDA method moves through several distinct steps (Figure. 4.1). Depending upon the problem being assessed, some of the steps may not be necessary (discussed further below).

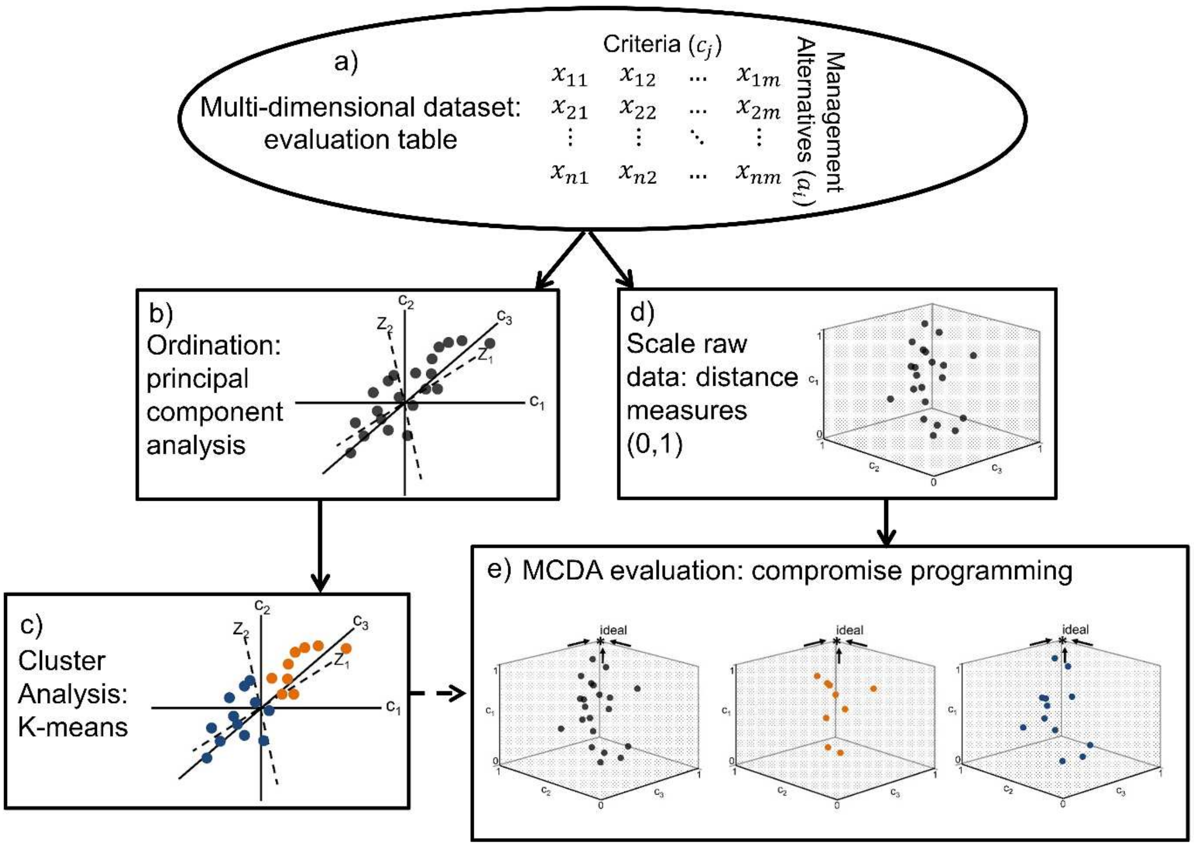

Figure 4.1 Conceptual diagram showing the five steps of the system of MCDA methods, showing (**a**) evaluation table, (**b**) statistical ordination, (**c**) cluster analysis, (**d**) re-scaling the raw criteria performance values, and (**e**) compromise programming. See text for further details.

Suppose a finite set of management alternatives $a_i(i = 1, \dots, n)$ each have a finite set of measurable water management criteria $c_j(j = 1, \dots, m)$. Each criterion is a proxy for socio-environmental river ecosystem health and the criterion performance value of a management alternative isx_{ij}. The $n \times m$ evaluation table forms the basis for the MCDA and method development (Figure. 4.1a).

Ordination is performed so that the multidimensional data may become easier to interpret. Principle component analysis (PCA) ordination is used to characterize the major variance explained in a multidimensional dataset by reducing the dimensionality of the problem to one or two indices called principal components $Z_m$that explain the most variation in the set (Figure. 4.1b). Quantitative measures of spread used in the PCA ordination method include:

Criterion mean:

$$\overline{c_j} = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \tag{4.1}$$

Distance between observed and mean criteria values:

$$D_{ij} = x_{ij} - \overline{c_j} \tag{4.2}$$

Criteria variance:

$$var(j) = \frac{1}{n-1}\sum_{j=1}^{m} D_{ij}^2 \tag{4.3}$$

Criteria standard deviation:

$$stdv(j) = \sqrt{var(j)} \tag{4.4}$$

Criteria covariance:

$$cov(i,j) = \frac{1}{m-1}\sum_{j=1}^{m}(x_{ij} - \bar{x})(\,x_{ij} - \bar{x}) \tag{4.5}$$

A square variance-covariance matrix A is developed with diagonal elements equal to the sample variances of each criterion and off-diagonal elements equal to the sample covariance of all possible pairs of criteria performance values:

$$A = \begin{bmatrix} var(1) & cov(1,2) & \dots & cov(1,m) \\ cov(2,1) & var(2) & \dots & cov(2,m) \\ \vdots & \vdots & \ddots & \vdots \\ cov(n,1) & cov(n,2) & \dots & var(m) \end{bmatrix} \tag{4.6}$$

The PCA next uses eigenvalue analysis to estimate a vector $\vec{v}$ that satisfies $A\vec{v} = \lambda\vec{v}$, where $\vec{v}$ are the m eigenvectors of matrix A, and λ are the corresponding eigenvalues. The eigenvalues are associated with new variables called principal components Z_m. The principal components are used to characterize the variance explained in the raw dataset. The eigenvectors associated with each principal component are used as coefficients in linear combinations with the raw criteria performance values. Each scaled ordination value is called a Z_m-score. Development of the principal components and Z_m-scores reduces the dimensionality of the original dataset so that one or two components explain most of the variation. The dominant eigenvalue λ_1 and its corresponding eigenvector v_1 explain the most variation in the set of management alternatives. The corresponding dominant components Z_1 and Z_2 represent the highest variation in the alternatives.

Statistical ordination is a critical procedure that is largely missing in MCDA evaluations of large numbers of management alternatives, particularly nondominated sets of alternatives that result from multi-objective optimization models, where moving from one alternative to the next improves at least one criterion performance value but not all (e.g., Pareto frontier graphs). However, large numbers of alternatives are difficult to organize and evaluate for decision-making. The PCA reduces the dimensionality of the problem so that the MCDA can concentrate on management alternatives that provide the greatest differences in outcomes for similar criteria (see below). For this reason, it is important that the PCA ordination provides maximum separation of the alternatives. Stewart (1981) suggests that the dominant component Z_1 explain at least 90% of the variation in the alternatives for the PCA to be useful.

After performing the PCA, the method aims to find a structure with the spread of management alternatives. This helps to discover potential tradeoffs among the management criteria. We use an objective cluster analysis of the principal component scores from the PCA (Figure 4.1c). The K-means algorithm (MacQueen, 1967) is used because its quantitative foundation is simple in that it is based on geometric distance metrics, it is very common, and it can be calculated efficiently using a variety of common computer programs. For this method, the iterative K-means algorithm is used to generate clusters such that the squared difference (i.e., Euclidean distance) between the empirical mean of each cluster and the points inside the cluster are minimized (Jain, 2010).

After the cluster analysis, the raw criteria performance values of the alternatives in each cluster are partitioned into two separate datasets. In effect, the tradeoffs in raw criteria performance values are characteristically featured in each cluster. Brans and Mareschal (2005) presumed that criteria expressing similar performance values are oriented along the PCA axes. This latent point is why PCA is a required component of the method. In other words, bypassing the PCA ordination and using clustering techniques from the multidimensional data directly fail to provide clusters with similar criteria tradeoffs unless the dataset is naturally correlated (discussed further below).

The next step in this method is to perform a formal MCDA evaluation. First, multidimensional datasets may have criteria performance values that range widely. Therefore, I use normalized (0-1) fuzzy distance measures to scale the values of the raw dataset so that each datum is a proportion of the highest achievable criterion value in the set (Figure. 4.1d). Compromise programming (Zeleny, 1973) is then performed on the full set of water management alternatives and on each cluster of alternatives to complete the prioritization (Figure. 4.1e). The graphical compromise programming algorithm organizes large datasets with conflicting criteria tradeoffs to a priority list of alternatives that are as close as possible (e.g., Euclidean distance) to an "ideal" but non-feasible alternative (coordinate 1,1,1 in Figure. 4.1e).

The following problem formulation was used for compromise programming based on incorporating the scaled data into the calculations:

$$\min L^p(i) = \sum_{j=1}^{m} w_j^p \left|1 - x_{ij}\right|^p \qquad (4.7)$$

where w_j^p is the criterion weight for criteria *j*, alternatives i. Closeness is based on using the family of distance metrics p. For this method, the ideal criterion value is equal to unity (1) and the Euclidean distance norm is used as an appropriate distance metric (*p*=2).

By performing the compromise programming method using equal criteria weights, this system of methods results in a set of preferred water management alternatives, where the priority alternatives from each cluster display characteristic tradeoffs (i.e., social preferences) of the management criteria. The MCDA evaluation of each cluster can be investigated alongside the traditional preference-neutral compromise programming evaluation of the full set of management alternatives for a more complete and transparent tradeoff analysis to deliver to decision makers (Figure 4.1e).

Illustration of the methods: Goulburn River, Victoria, Australia

The Goulburn-Broken River catchment lies within the Murray-Darling Basin (Figure 4.2a). The region supports agriculture (both dryland and irrigated), food processing, forestry and tourism industries. Although it only makes up 2% of the Murray-Darling Basin's land area, the catchment generates 11% of water resources for the basin. Mean annual discharge for the catchment is approximately 3,200 gigaliters (CSIRO 2008, http://www.clw.csiro.au/publications/waterforahealthycountry/mdbsy/pdf/Goulburn-snapshot.pdf), and approximately 50% of that is diverted to meet agricultural, stock and domestic demand.

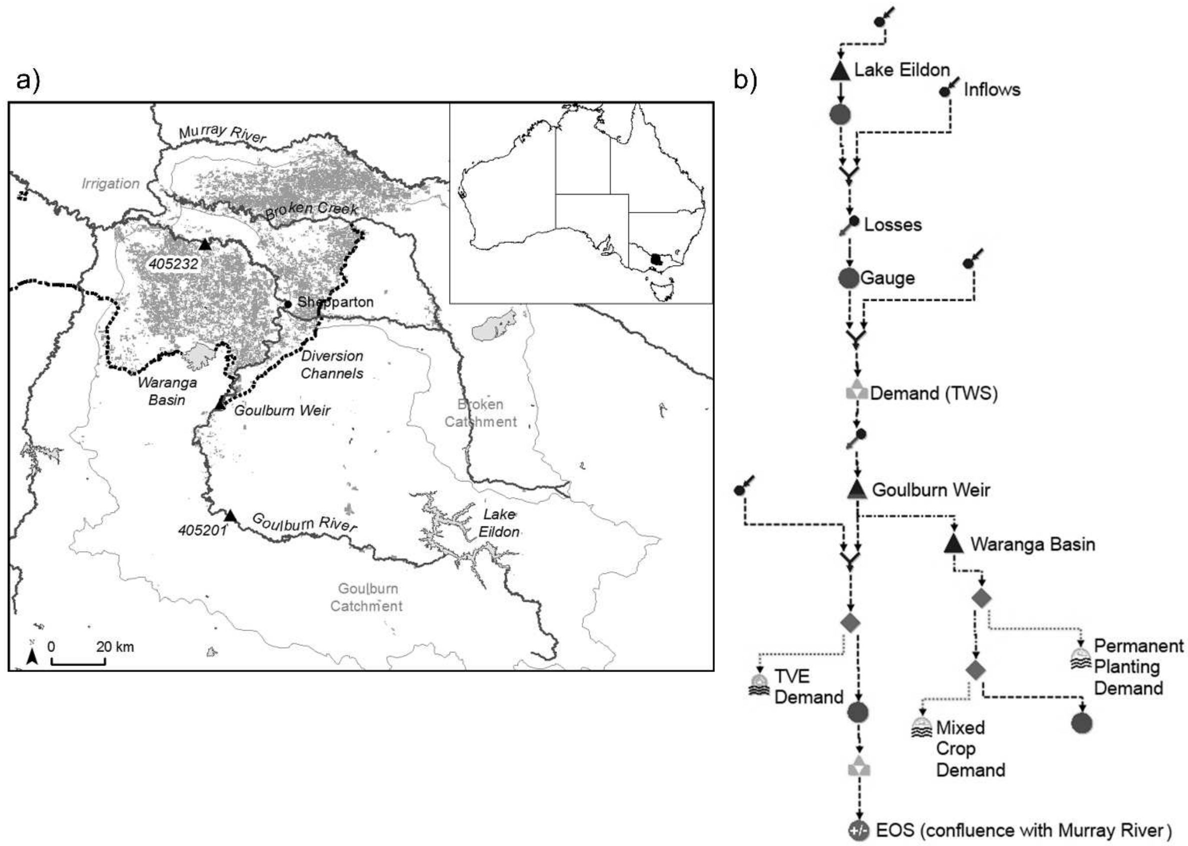

Figure 4.2 (**a**) Goulburn-Broken catchment map. (**b**) Simplified hydrologic network model for the system.

The incorporation of flow-ecology relationships into operational decision making for ecological water allocations (i.e., environmental flows) is a priority area of river management in Australia (Davies et al., 2014). The Goulburn River has received considerable state and federal investment in environmental flows to support improved ecological condition (e.g., Webb et al., 2015). A proof of concept approach was previously developed that used ecological response models for allocating environmental flows in the catchment (Powell et al., 2013). The prototype hydro-ecological predictive model used a validated quantitative response function linking the streamflow regime to the encroachment of terrestrial vegetation into the river channel (Webb et al., 2014). This model was coded for integration into a simplified link-node river management model (Figure 4.2b) provided by the Source Integrated Water Resource Modelling framework, hereafter called Source (Welsh et al., 2012, http://ewater.com.au/products/ewater-source/). The Source model used daily discharge, rainfall and evaporation data for the period 1901 to 2012 to calibrate inflows for the link-node network and it was used to simulate ecological responses to changing environmental flow demands throughout the catchment. The resulting flow-ecology response model simulates the river segment inflows, system operations, water storages, flow management, ecological response and consumptive demands within the Goulburn-Broken system that is linked to climate (see Powell et al., 2013). Although it was a proof of concept, the research was performed to provide ecologically defensible models (derived by considering available evidence from many sources) for integration into other hydrological river management models to support balanced river management and policy decisions.

Criteria development and evaluation table

The previously calibrated hydro-ecological response model and other custom models were integrated with the Source model to simulate catchment inflows, system operations, environmental flows and irrigation demands (based on crop water use) at a range of spatial and temporal scales. To summarize this process, a set of rules (i.e., decision variables) were developed to deliver environmental flows to suppress the encroachment of terrestrial vegetation into the river channel. These rules include the antecedent flows, the existing terrestrial vegetation within the channel, season, and the volume of water held in storage that is available for environmental flows. Next, five criteria were developed to represent flow-ecology response (terrestrial vegetation encroachment), net irrigation benefit and total water allocated to suppress vegetation encroachment (Table 4.1). The irrigation criteria C_1 and C_2 were based on values extracted directly from an internal resource assessment model within Source and calculation of annual net benefits over the relevant irrigation nodes in the catchment network, respectively. Criterion C_2 was developed to maximise the average annual net benefit I over the combined irrigation nodes (\$ ha^{-1} yr^{-1}). The average annual net benefit is the sum of net benefit for each crop *a* for each year *y*, where net benefit is a function of area planted *AP*, yield *Y*, the price *P*, input costs *C*, volume of water *V*, and cost of pumping *CP*.

$$I = \frac{\sum_{a=o}^{n\ years} \sum_{c=0}^{crop} [(AP_{ac} * Y_c * P_c) - (AP_{ac} * C_c) - (V_{ac} * CP)]}{n * A_{max}} \qquad (4.8)$$

The hydro-ecological criteria C_3 and C_4 were based on the previously developed flow-ecology response model and rules for the catchment. Criterion C_5 was developed to minimize the total possible water allocation for environmental flows, which indirectly benefits water allocations for consumptive (e.g., irrigation) uses in the catchment.

Table 4.1 List of criteria for water allocation planning in the Goulburn-Broken River catchment (*Source:* Powell et al., 2013).

Criterion	*Goal*	*Units*
C_1 water extracted for irrigation	maximize	gigaliters per year (GL yr^{-1})
C_2 net benefits to irrigation	maximize	\$AUS per hectare per year (\$ ha^{-1} yr^{-1})
C_3 average spring terrestrial vegetation encroachment into river channel	minimize	percent (%)
C_4 maximum spring terrestrial vegetation encroachment into river channel ("mini-max" criterion)	minimize	percent (%)
C_5 water allocation to suppress terrestrial vegetation encroachment	minimize	gigaliters per year (GL yr^{-1})

A nondominated sorting genetic algorithm NSGA-II (Deb et al., 2002) was integrated into the Source model as a dynamic simulation and multi-objective optimization procedure for water allocation in the Goulburn-Broken catchment. Genetic algorithms are special kinds of evolutionary algorithms that are based on the mechanics of natural selection and genetics (Goldberg, 1989). A typical genetic algorithm is a multipath search procedure based on the development of heuristic search rules and quantitative investigation of "generations" of management alternatives. For the case study, the iterative optimization procedure included Source model scenario development for daily water allocation schedules over 24 years using historic inflows and simplified climate data. The case study period (1988-2012) represents a sequence of dry and wet periods in the catchment. The NSGA-II used an initial stochastic water allocation scenario throughout the catchment that was intended to benefit the management criteria based on criteria goals (Table 4.1). The initial scenario routed the responses of each criterion at relevant nodes through the catchment to a pre-defined catchment outlet and the cumulative response was recorded for each criterion. Between each scenario run, the cumulative criteria performance values at the catchment outlet were compared and the scenario run that met the criteria goals were kept and recorded. The iterative process converged on 151 nondominated scenarios (Table 4.2), hereafter referred to as water allocation alternatives.

Table 4.2 Incomplete evaluation table of numbered water management alternatives for multidimensional MCDA evaluation. Each management alternative is a different 24-year daily schedule of water allocations throughout the Goulburn catchment to benefit the management criteria. The cumulative criteria performance values are displayed.

Alternative number	C_1 (GL yr^{-1})	C_2 (\$ ha^{-1} yr^{-1})	C_3 (%)	C_4 (%)	C_5 (GL yr^{-1})
1	749	2,901	11	28.5	12
2	662	2,704	2.4	12.6	283
3	697	2,779	4.3	12.6	130
4	749	2,895	11.1	28.5	0
5	749	2,901	11.2	28.5	12
…	…	…	…	…	…
151	731	2,871	9.2	19.8	27

The evaluation table of nondominated water allocation alternatives is complex. Visualizing the tradeoffs in these values is a good way to summarize the complexity of the system to decision makers for making water allocation decisions. However, the table is large and difficult to interpret and therefore problematic to prioritize without structured decision making methods. In response to this issue, additional MCDA analyses can be performed to make the decision process more transparent for stakeholders and analysts using the described method.

Ordination and cluster analysis

Following development of the described method (Figure. 4.1), ordination using PCA was applied to project the alternatives onto a two-dimensional plane (Figure. 4.3). The resulting principal component Z_1-scores provided maximum separation (93%) of the dataset followed by Z_2-scores (7%). Upon inspection, six alternatives appeared as possible outliers (upper left alternatives in Figure. 4.3). Although it appears that the 7% variance on the small difference in scale along the Z_2 axis may explain the distribution of the possible outliers, I performed the successive MCDA evaluation with and without them to validate the results.

The K-means cluster analysis was performed on the principal component Z_1- and Z_2-scores, specifying two clusters to be generated using the cluster package (Maechler et al., 2014) in the R programming environment. The results yielded 75 alternatives in Cluster A and 61 alternatives in Cluster B (Figure. 4.3).

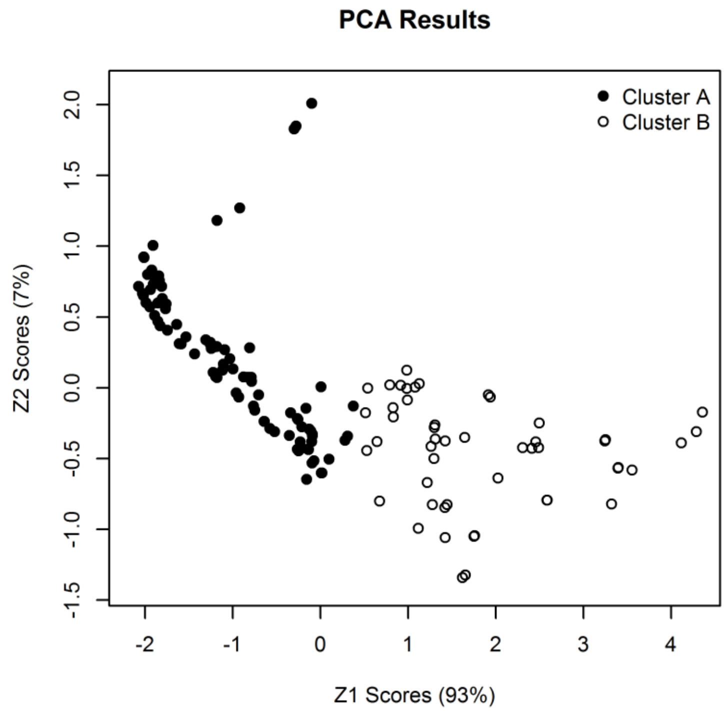

Figure 4.3 Principle component analysis ordination of the 151 nondominated water management alternatives. Percent variance explained for each axis is in parentheses (note difference in scale for the two axes). Cluster analysis partitioned the alternatives into two groups that tradeoff conflicting irrigation and hydro-ecological criteria performance values.

Tradeoff assessment of clusters

After the cluster analysis, the raw criteria values inside each cluster were inspected. Cluster A included alternatives with better irrigation values for C_1, C_2, and C_5, whereas Cluster B included alternatives with better hydro-ecological values for C_3 and C_4. Therefore, the criteria tradeoffs among the two clusters is understandable and an MCDA evaluation on each cluster was believed to yield alternatives for decision makers interested in better long-term irrigation outcomes and, alternatively, better hydro-ecological performance throughout the catchment.

MCDA evaluation

After re-scaling the raw criteria performance values in the full multidimensional dataset and in each cluster, compromise programming was performed on the full set of water allocation alternatives and each cluster individually (Table 4.3). An additional compromise programming iteration was performed on Cluster A without including six possible outliers described above. Yet the same highest ranked results were retained with or without those alternatives and so this additional iteration is not considered further.

Table 4.3 Rankings from each iteration of the compromise programming evaluation. The top ten ranked alternatives and their scaled criteria performance values are shown.

Rank	Preference-neutral compromise						Cluster A (alternatives with better irrigation performance)					
	Alternative number	C_1 Maximize water for irrigation	C_2 Maximize net irrigation benefit	C_3 Minimize average springe TVE	C_4 Minimize maximum spring TVE	C_5 Minimize water delivered to suppress TVE	Alternative number	C_1 Maximize water for irrigation	C_2 Maximize net irrigation benefit	C_3 Minimize average springe TVE	C_4 Minimize maximum spring TVE	C_5 Minimize water delivered to suppress TVE
1	146	0.57	0.58	0.63	0.88	0.82	62	0.92	0.88	0.33	0.52	0.97
2	121	0.57	0.58	0.61	0.88	0.83	56	0.91	0.88	0.33	0.51	0.97
3	81	0.54	0.58	0.62	0.88	0.86	59	0.89	0.85	0.31	0.59	0.95
4	92	0.56	0.55	0.64	0.88	0.82	139	0.93	0.91	0.27	0.52	0.95
5	143	0.56	0.55	0.64	0.88	0.82	46	0.90	0.88	0.31	0.49	0.95
6	47	0.58	0.70	0.47	0.86	0.82	132	0.94	0.94	0.22	0.52	0.99
7	104	0.59	0.61	0.52	0.84	0.80	42	0.95	0.91	0.24	0.48	0.98
8	141	0.71	0.79	0.36	0.74	0.87	108=115	0.76	0.85	0.34	0.68	0.88
9	130	0.58	0.67	0.48	0.85	0.78	117	0.96	0.94	0.22	0.47	0.99
10	29	0.59	0.61	0.51	0.80	0.85	109	0.83	0.85	0.28	0.56	0.91

Scaled values are a proportion of the highest achievable and, therefore, values closer to unity (1) are better water allocation schedules for the criterion.

Table 4.3 *continued*

Rank	Cluster B (alternatives with better hydro-ecological performance)					
	Alternative number	C_1 Maximize water for irrigation	C_2 Maximize net irrigation benefit	C_3 Minimize average springe TVE	C_4 Minimize maximum spring TVE	C_5 Minimize water delivered to suppress TVE
1	36	0.40	0.40	0.86	1.00	0.58
2	3	0.40	0.40	0.78	1.00	0.54
3	112	0.49	0.52	0.65	1.00	0.70
4	93	0.45	0.52	0.66	0.99	0.57
5	69	0.36	0.46	0.70	1.00	0.55
6	85	0.36	0.34	0.71	1.00	0.69
7	17	0.39	0.37	0.68	0.93	0.62
8	26	0.36	0.46	0.66	0.99	0.54
9	72	0.40	0.40	0.73	0.78	0.58
10	16	0.28	0.34	0.75	0.93	0.61

The three sets of ranked alternatives are each unique perspectives to inform decision making. The described method is an objective set of procedures to deliver priority information to stakeholders under the important caveats that the iteration on the full multidimensional dataset provides a preference-neutral compromise among the problem criteria. Cluster A rankings are alternatives with water allocation schedules that largely benefit irrigation in the catchment and Cluster B rankings are alternatives with schedules that largely benefit the hydro-ecology of the catchment. Therefore, stakeholders who value irrigation more than ecological health can use the Cluster A rankings as appropriate alternatives for planning and, conversely, stakeholders who value ecological health more than irrigation can deliberate among the alternatives in the Cluster B rankings.

Formal stakeholder deliberation of the ranked alternatives is beyond the scope of this chapter. However, investigating the socio-environmental tradeoffs in the ranked datasets is important so that stakeholders may be given useful information from which to base decisions. Based on a limited investigation of Table 4.3, it is apparent that the differences in the tradeoffs of criteria values in the alternatives becomes more distinct in proportion to the “ideal” values (1) after the first several ranked alternatives are screened (Table 4.3). For example, significant changes in the tradeoffs of criteria C_2 and C_3 occur between the 5th and 6th highest ranked alternatives from the preference-neutral compromise iteration and the water allocation schedules through the catchment become more imbalanced. Criteria values for C_2 changed from 55% of highest achievable to 70% and values for C_3 changed from 64% to 47%. Likewise, significant improvements in criteria C_1 and C_2 values come at a cost of reducing the performance values of criterion C_3 significantly between the 5th and 6th highest ranked alternatives in Cluster A. In sum, stakeholders may find deliberation among the top five ranked alternative water allocation schedules sufficient for balanced water management in the catchment.

Testing the method on other multidimensional datasets

The described method works well for the case study presented, but does it work for other multidimensional sets of criteria and alternatives? I provide three latent points to address this question. First, I ask if the PCA can offer an appropriate spread of alternatives in a way that cluster analysis is useful. The method was tested on a number of published water management datasets (e.g., Duckstein and Opricovic, 1980; Mareschal and Brans, 1988; Chung and Lee, 2009; Hermoso et al., 2015). Successful cluster analysis, when combined with a differentiation in criteria tradeoffs resulting from the PCA, was achieved when the percentage of variance explained in the ordination procedure is high enough to spread the data onto the PCA axis. I agree with Stewart (1981) supposition that 90% variance explained by the dominant principle component is a good threshold. However, sometimes there is inherent spread and correlation in the raw multidimensional dataset and the full method is not useful for case studies with only two or three criteria because the raw data tend to be spread appropriately (see Hermoso et al., 2015; Chapter 3). In these cases, the cluster analysis can be undertaken directly upon the normalized criteria scores and ordination (Figure. 4.1b) is not necessary.

A second and related concern is how to address questions of cluster validity (Jain, 2010). That is, how can the cluster analysis classify the management alternatives in a way that criteria tradeoffs are distinguishable inside each individual cluster? By testing the described method on the published and unpublished datasets I conclude that cluster analyses are more valid when there are high numbers of alternatives. MCDA problems with small numbers of alternatives (e.g., five management alternatives in Duckstein and Opricovic, 1980) do not require cluster analysis because the PCA places the management alternatives into well-defined graphical regions that are sufficient for prioritizing tradeoffs (i.e., natural clusters exist).

A third concern is the number of clusters to develop from the ordination data. In general, specifying clusters for prioritizing management alternatives is highly subjective and dependent on stakeholders having to consider mutually contradictory sets of choices. The method aims to identify characteristic tradeoffs for MCDA evaluation and subsequent decision making; more clusters will likely muddle stakeholder deliberations. Through testing the method on other datasets I found that it is harder to describe characteristic tradeoffs using cluster analysis when the problem has fewer alternatives because the PCA can project natural clusters on the one hand, or if more clusters are defined around the data on the other hand. Based on this point, two clusters were developed in the illustration because there were two regions of criteria tradeoffs (irrigation benefits and ecological response) along the Z_1 axis, which is easier for stakeholders to interpret than establishing more clusters.

Sensitivity analysis to test the boundaries of the method

Can the method complement subjective MCDA evaluations that use criteria weighting schemes? That is, can the compromise programming results (Table 3) be validated against traditional preference-neutral compromise programming iterations of the full multidimensional dataset that use a numerical weighting approach to the criteria? To address these questions, a limited sensitivity analysis was conducted to infer whether the objective MCDA evaluation on the clusters produces similar results to subjective evaluations that use different criteria weighting schemes, both for the case study dataset, and other tested datasets.

In order to design the sensitivity analysis, a systematic procedure for developing weighting scenarios was conducted. For a preference-neutral (i.e., equal weight) MCDA evaluation of the full dataset, the five criteria are each given 20% of the weighted importance; the three irrigation criteria are given 60% of the weighted importance and the hydro-ecological criteria given 40%. Therefore, to simulate preferences on the irrigation criteria like Cluster A, seven compromise programming iterations on the full scaled dataset were performed where the three irrigation criteria were given a higher proportion of weight than the two hydro-ecological criteria in 5% intervals (Table 4.4). Likewise, to simulate preferences on the hydro-ecological criteria like Cluster B, seven iterations were performed on the full scaled dataset where the hydro-ecological criteria were given higher weights in 5% intervals. This was performed to generate rankings and to compare them with the results of the MCDA evaluation of clusters (Table 4.5).

The highest ranked water management alternative in Cluster A (alternative 62 in Table 4.3) was consistent with giving the three irrigation criteria between 70-80% of the weighted importance equally (Table 4.4). On more extreme ends of the preference spectrum (i.e., giving irrigation criteria between 60-70% and 85% or greater), the top five highest ranked alternatives dropped off and were replaced by others. Likewise, the highest ranks for Cluster B were consistent with giving the hydro-ecological criteria at least 60% of the importance in the sensitivity iterations. Prior to this threshold (i.e., between 40-60%), the second highest ranked alternative (146) was the priority found by the compromise programming.

These results yield an incomplete validation to the described method as a complement to using subjective elicitation procedures for MCDA evaluation. In general, I found both corroboration and inconsistencies. The inconsistencies occurred on datasets of smaller sizes. The sensitivity analysis does not take into account the likely un-equal importance weights given to similar criteria. Nevertheless, the intention for the method is to complement but not replace subjective elicitation procedures and I desire for similar kinds of sensitivity analyses on future case studies to shed more light on the robustness of the method against subjective MCDA evaluations using alternative weighting schemes for management criteria.

Table 4.4 Weighting schemes in preference-neutral compromised programming sensitivity analysis of the full dataset of management alternatives.

Criteria	**High proportion of weight on irrigation criteria (C_1, C_2, C_5)**							**High proportion of weight on hydro-ecological criteria (C_3, C_4)**						
	SA1 (65%)	SA2 (70%)	SA3 (85%)	SA4 (80%)	SA5 (85%)	SA6 (90%)	SA7 (95%)	SA8 (45%)	SA9 (50%)	SA10 (55%)	SA11 (60%)	SA12 (65%)	SA13 (70%)	SA14 (75%)
C_1	0.2167	0.233	0.25	0.2667	0.2833	0.3	0.3167	0.1833	0.1667	0.15	0.133	0.1167	0.1	0.0833
C_2	0.2167	0.233	0.25	0.2667	0.2833	0.3	0.3167	0.1833	0.1667	0.15	0.133	0.1167	0.1	0.0833
C_3	0.175	0.15	0.125	0.10	0.075	0.05	0.025	0.225	0.25	0.275	0.3	0.325	0.35	0.375
C_4	0.175	0.15	0.125	0.10	0.075	0.05	0.025	0.225	0.25	0.275	0.3	0.325	0.35	0.375
C_5	0.2167	0.233	0.25	0.2667	0.2833	0.3	0.3167	0.1833	0.1667	0.15	0.133	0.1167	0.1	0.0833

Note: each column of weights sum to unity (1)

Table 4.5 MCDA sensitivity analysis results. Results from the MCDA evaluation of clusters (Table 3) is included for comparison. The highest ranked alternative from each cluster is indicated in bold face in the sensitivity analysis results.

Rank	Cluster 1	SA1	SA2	SA3	SA4	SA5	SA6	SA7	Cluster 2	SA8	SA9	SA10	SA11	SA12	SA13	SA14
1	**62**	108=115	**62**	**62**	**62**	132	25	25	**36**	146	146	146	**36**	**36**	**36**	**36**
2	56	141	59	56	56	117	117	60	146	121	81	143	146	3	3	71
3	59	51	56	59	139	139	132	117	143	81	143	92	143	123	123	20
4	139	59	108=115	139	132	**62**	42	98	3	143	92	81	92	112	71	123
5	46	**62**	139	46	59	42	102	43=77	92	92	121	121	3	15	19	19
	Note: alternative 62 ranked 12th in SA6 and 31st in SA7								*Note: alternative 36 ranked 26th in SA8, 10th in SA9, 6th in SA10,*							

Concluding remarks

In this chapter, a new system of methods is described to objectively provide meaningful prioritizations of water management alternatives that can be performed on large sets of alternatives and criteria prior to negotiating with decision makers. The value of the method is demonstrated by the fact that I performed seemingly subjective evaluations on the water allocation alternatives (in the case study, prioritizing options that favored either irrigation or hydro-ecological criteria) without requiring elicitation of criteria weights. The method is particularly useful with large multidimensional datasets of management alternatives and criteria like nondominated solutions to multiobjective optimization methods. Results of the MCDA evaluations are communicated to decision makers in the same way as other methods, but with this method, the specification of importance of conflicting criteria can be made objectively through the described procedures.

Method development of this kind is limited in the MCDA literature (Belton and Stewart, 2002; Figueira et al., 2005), and applications in the water management field are rare. Yet, sustainable water management will require managers to deal with larger and more complex real-world problems and, hence, the dimensionality of future water management MCDA tradeoff analysis will grow. Describing the multi-disciplinary tradeoffs among management criteria to decision makers without using this method will be difficult because they can only be described graphically or in tabular form and they do not include formal prioritization procedures to organize and filter the alternatives. Likewise, stakeholders may be more hesitant to offer subjective preferences to the components of complex multidimensional problems if its dimensionality and extraneous factors (e.g., climate change, financial risk) grow. It is in these areas of research and development that the method is likely to prove most useful.

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